

# Occupation Specificity and the Decline in the Aggregate Job Separation Rate

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## Abstract

The long-run decline in the aggregate job separation rate in the United States has been documented in the literature. This paper proposes that the increase in occupation-specific training, which results in human capital becoming less transferable across occupations, explains the falling aggregate job separation rate. I do a shift-share decomposition of the decline in the aggregate job separation rate to find that it is accounted for mostly by the within-occupation increase in required occupation-specific training. Then I build a search-and-matching model where the increase in occupation-specific training within occupations reduces job separations. The model predicts 60% of the decline in the aggregate job separation rate. When occupations become more specific, human capital acquired from one occupation becomes less transferable to another, resulting in larger wage cuts for occupation switchers. Occupation switchers must also undergo a longer period of occupation-specific training in their new occupation, during which they earn low wages. In the model, after occupations become more specific, workers separate less to avoid switching occupations, accepting lower wages at their current job at the same level of productivity.

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# 1 Introduction

Previous literature has documented a decline in “labor market fluidity” (e.g., employment-to-unemployment transitions, job-to-job transitions, formation of new firms, and geographic movement across labor markets) in the United States over the past four decades. This paper focuses on the decline in the aggregate job separation rate (the employment-to-unemployment transition rate). Understanding what is causing this decline is important because it could have either good or bad implications for the economy (Hyatt and Spletzer 2013, Molloy et al. 2016). On the one hand, declining dynamics could signal increasing costs of labor market transitions seeking the most productive matches. On the other hand, it could indicate the lesser need to make these transitions due to better worker–firm match quality and the associated higher wages.

This paper proposes that the fall in the transferability of human capital across occupations, resulting from the increase in the amount of required occupation-specific training, explains the decline in the aggregate job separation rate.

I start the empirical analysis by combining labor market data from the Monthly Current Population Survey (CPS) with the required length of occupation-specific training by occupation from the U.S. Department of Labor’s Dictionary of Occupational Titles and O\*NET. I make two observations. One is that the required amount of occupation-specific training increased (“increase in specificity”) within occupations over time. The other is that holding specificity fixed, employment shifted towards occupations requiring more occupation-specific training (“more specific occupations”) that have lower job separation rates. Through a shift-share decomposition, I find that the within-occupation increase in specificity is the primary driver of the decline in the aggregate job separation rate. Moreover, the group of occupations that at first required minimal specific training (“initially not specific”) and have become more specific over time (compared to occupations that already required specific training four decades ago) accounts for half the decline in the aggregate job separation rate.

Using the Survey of Income and Program Participation (SIPP), I confirm previous findings in the literature that human capital is largely occupation-specific; the observed average wage loss after an unemployment spell is mostly experienced by occupation switchers. What I further find is that this wage loss increases when their previously held occupation requires more occupation-specific training. I interpret this as evidence that the human capital of workers in an occupation that requires more occupation-specific training is more specific to the given occupation and less transferable to a different occupation. When workers switch occupations, those who previously worked in occupations that required more specific training will find less of their previous human capital carried over to the new occupation. This greater loss of occupation-specific capital manifests as larger wage cuts after an unemployment spell for these occupation switchers who previously worked in an occupation requiring more occupation-specific training. Therefore, throughout the paper, I use the term “occupations that are more specific” to denote occupations that require more occupation-specific training and the term “increase in specificity” to denote the increase in the required amount of occupation-specific training.

Motivated by my empirical analysis, I then build a search-and-matching model to learn how the increase in specificity within occupations explains the decline in the aggregate job separation rate. The main ingredients are endogenous job separations and occupation-specific human capital that workers acquire during employment and lose when they switch occupations. My model has two occupation specificity parameters: (i) the average duration of occupation-specific training and (ii) the output gap by which nontrained workers are less productive because they have not yet acquired the occupation-specific capital. To ask my model how much of a decline it predicts in the aggregate job separation rate when occupations become more specific, the occupation specificity parameters in the model are increased to match the increase in occupation specificity in the data. The increase in the average duration of occupation-specific training matches the required length of occupation-specific training from the Dictionary of Occupational Titles and O\*NET. The increase in the output gap is informed by the estimated increase in the wage penalty faced by occupation switchers (relative to non-occupation switchers) when their previously held occupation requires more occupation-specific training, obtained from the SIPP. The model predicts 60% of the decline in the aggregate job separation rate. It also captures my empirical finding that the occupations that were initially nonspecific and have become more specific over time contribute the most to the decline in the aggregate job separation rate.

Why do workers choose to separate less? In my model, occupations become more specific by the increase in (i) the average duration of occupation-specific training that nontrained workers must undergo to acquire the occupation-specific capital and become trained in the occupation or (ii) the output gap by which nontrained workers are less productive because they are not trained yet. When occupations become more specific, workers choose to separate less from their job to avoid switching occupations later. If they switch occupations, they would experience larger wage cuts because previous occupation-specific human capital becomes less transferable to other occupations. They also accept lower wages at their current job at the same level of productivity as they become more reluctant to separate from their job.

The implications of occupation specificity from my analysis are relevant to the current COVID-19 pandemic. One narrative explains that the lack of transferability of human capital across occupations is holding back the recovery in employment.<sup>1</sup> The following passage from a *Wall Street Journal* article (Hilsenrath and Cambon 2021) reflects this narrative:

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<sup>1</sup>Motivated by this narrative, my companion paper analyzes the role of increasing occupation specificity in the rise in the average unemployment duration observed in the United States. The intuition is that unemployed workers who are previously trained in occupations that have become more specific become more attached to their previous occupation. Their human capital becomes less transferable to a different occupation, which leads to larger wage cuts in the event of an occupation switch. Therefore, they increasingly choose to not switch occupations, leading to longer unemployment spells.

Robin Taylor, of Desert Hills, Arizona, is an example. He was organizing large corporate meetings for pharmaceutical drug launches before Covid-19 hit and shut down many in-person gatherings. Mr. Taylor, who had worked in the corporate events industry for 35 years, was laid off in March of 2020.

He has been sending out his résumé four to 10 times a week, but many jobs that would suit him, including project management, events coordination and production, aren't coming back yet, he said.

“Yes, Amazon has got drivers all over the place,” said Mr. Taylor. “All of us are not trained for those jobs. So as far as I'm concerned, I'm having a tough time coming back.”

As presented in an article from *The Washington Post* (McGregor 2020), there is also anecdotal evidence that workers have been working longer hours during the pandemic, presumably at the same or lower salary, out of fear of being laid off. All of this is relevant to my model's implication that incumbent workers who anticipate the possibility of becoming like Mr. Taylor, that is, facing the possibility of not being reemployed in the same occupation after becoming unemployed, accept lower wages at their current job to avoid job separation. Given that occupations are becoming more specific and workers are accumulating occupation-specific capital, my analysis points to the need for policies such as worker retraining that facilitate the reallocation of workers between different occupations. Such policies would help ensure that existing worker–firm matches are the most productive matches, and incumbent workers earn higher wages (instead of having to accept lower wages).

## Contributions to the literature

This paper contributes to three strands of literature.

First, this paper contributes to the literature on the source of the declining job separation rate. Papers such as Hyatt and Spletzer (2013) and Molloy et al. (2016) have documented the decline in various measures of labor market dynamics. They also examined and ruled out various hypotheses, including changes in the composition of worker demographics and firm characteristics. Fujita (2018) proposes that the decline in the aggregate job separation rate is a result of an exogenous increase in the probability of skill loss during unemployment, which in his model is increased to match the increase in the rate of occupation switching out of employment over time observed in the data. Cairó (2013) and Cairó and Cajner (2018) hypothesize that an increase in the cost of employer-specific training reduces job separations. My model explicitly introduces occupations and occupation-specific human capital. Human capital is occupation-specific; it is not necessarily lost after job separation but is lost after switching occupations. This is motivated by previous literature like Kambourov and Manovskii (2009a), who point to human capital being mostly occupation-specific instead of employer-specific. I also find evidence from the SIPP (see the appendix) that the decline in wages faced after an unemployment spell is determined from switching occupations, not from switching employers. My model uses two occupation specificity parameters: (i) the average duration of occupation-specific training and (ii) the output gap by which nontrained workers are less

productive because they have not yet acquired the occupation-specific capital. In my experiment, to predict the decline in the aggregate job separation after occupations become more specific, I increase the two occupation specificity parameters to match the increase in the wage loss associated with occupation switching when the previously held occupation becomes more specific (which reflects the increase in the loss of occupation-specific capital) and occupations' increase in the required amount of occupation-specific training as defined in the Dictionary of Occupational Titles and O\*NET.

Second, this paper contributes to the literature on occupation-level labor market outcomes. Papers such as Kambourov and Manovskii (2009a) have documented that human capital is largely occupation-specific; wages are primarily determined by occupational tenure instead of tenure with an industry or employer. In other data sets, Huckfeldt (2016) and Gathmann and Schönberg (2018) document that wage losses are concentrated among occupation switchers after an unemployment spell. I also find in the SIPP that occupation switchers, as opposed to non-occupation switchers, face wage losses after an unemployment spell. In the context of increasing occupation specificity, I further find this wage loss associated with occupation switching increases when the previously held occupation becomes more specific. The increasing wage penalty observed by occupation switchers, and not by non-occupation switchers, reflects the increase in the loss of occupation-specific capital after switching occupations after occupations become more specific. This result is used to discipline the increase in the occupation specificity parameters in my model and predict the decline in the aggregate job separation rate.

Third, this paper contributes to the literature on search-and-matching models with occupation-specific human capital. Previous literature analyzed the role of occupation-specific human capital in the increase in wage inequality (Kambourov and Manovskii 2009b), the increase in unemployment duration (Wiczer 2015), and the amplification of unemployment over business cycles (Carrillo-Tudela and Visschers 2017). My model borrows the model framework in Carrillo-Tudela and Visschers (2017) and adds the notion of increasing occupation specificity to study the effect of increasing occupation specificity on the long-run decline in the aggregate job separation rate.

## **Roadmap**

The rest of the paper is organized as follows. In Section 2, I combine labor market data from the CPS and SIPP with data on the required amount of occupation-specific training by occupation from the Dictionary of Occupational Titles and O\*NET. Then I do a shift-share decomposition of the decline in the aggregate job separation rate. The shift-share decomposition motivates a model where the increase in the amount of occupation-specific training within occupations reduces job separations, which I build and calibrate in Section 3. I then discuss the model's mechanism and evaluate the model's performance in predicting the decline in the aggregate job separation rate. Section 4 concludes.

## 2 Empirics

### 2.1 Data

I collect the required length of occupation-specific training by occupation from the Dictionary of Occupational Titles (1977,1991) and the O\*NET (2000–2017, annual). In the Dictionary of Occupational Titles, it is labeled as specific vocational job preparation and rated on a nine-point scale. In O\*NET, job zones are rated on a five-point scale corresponding to specific vocational job preparation in the Dictionary of Occupational Titles. Throughout the paper, I collapse the nine-point-scale specific vocational job preparation (SVP) from the Dictionary of Occupational Titles (DOT) to the five-point-scale job zones, following the definition provided in O\*NET on how job zones correspond to SVP. Higher values represent a longer required length of occupation-specific training. In the main analysis, the five job zones (JZ) are aggregated into three levels (low (JZ = 1), medium (JZ = 2 or 3), and high (JZ = 4 or 5)). Following the DOT and O\*NET, occupations in low, medium, and high job zones require an average length of 8, 12, and 24 weeks of occupation-specific training, respectively. This results in a panel of job zones by occupation over time from 1977 to 2017.<sup>2</sup> This panel of job zones by occupation and year is then merged to the CPS (1983–2018) and SIPP (1985–2013) data.

The appendix discusses how job zones are defined, how they differ from general education and routine task intensity, and why job zones are a proxy for occupation specificity. In other words, occupations in higher job zones are “specific.” An occupation becoming more specific means that human capital acquired and used in this occupation becomes more specific to this occupation and less transferable to a different occupation. This follows the observation from the SIPP data that the wage decline after switching occupations after unemployment, as opposed to switching employers, is larger the higher the previous occupation’s job zone. This result (provided in the appendix) is used to discipline my model later in Section 3. Also, the probability of occupation switching after unemployment is lower the higher the previous occupation’s job zone (results provided in the appendix). These observations are consistent with the intuition that the human capital associated with occupations requiring more occupation-specific training is more occupation-specific and hence makes occupation-switching more costly. Throughout the paper, I often refer to the 1977 job zone (JZ1977), the earliest rating of occupation specificity, as an occupation’s “initial specificity” when discussing the increase in occupation specificity within occupations.

I use the Basic Monthly CPS data (1983–2018) for labor market outcomes, in particular job separation rates.<sup>3</sup> I use the SIPP data (1985–2013) for the aforementioned results on the increase in wage losses after an unemployment spell that occupation switchers experience (relative to non-occupation switchers) when their previously held occupation becomes more specific. This result is

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<sup>2</sup>Because the occupation specificity measure is not available for all periods pre-2000, the contemporary job zone of an occupation each period is assigned as follows. I assign the 1977 job zone to years 1983–1985, the 1991 job zone to years 1986–1995, and the 2000 job zone to 1995–2000. After 2000, when job zone ratings are available each year, the corresponding job zones are assigned to each year (the 2017 job zone is assigned for 2018).

<sup>3</sup>The Basic Monthly CPS data are downloaded from the NBER website (<http://www.nber.org/cps-basic/>). To link individuals over time, I merge the NBER dataset with the IPUMS CPS individual identifiers.

used to discipline the increase in occupation specificity in the model and predict the decline in the aggregate job separation rate.<sup>4</sup>

I follow Dorn (2009) and Deming (2017) to develop the balanced panel of occupation codes and obtain 338 occupation codes. A balanced panel of occupation codes is needed because I am using the increase in the specificity of an occupation over time. Dorn (2009) and Deming (2017) constructed occupation code crosswalks based on the 1980 Census codes and later. Hence the CPS data sample period in this paper starts from 1983.

## 2.2 Decomposing the decline in the aggregate job separation rate

The following subsections show that (i) employment increased in more specific occupations, which have lower job separation rates (“between-group effect”), and that (ii) occupation specificity within occupations has increased (“within-group effect”). Based on these observations, I do a shift-share decomposition to see which of the two observations, the “within-group effect” or “between-group effect,” accounts for more of the aggregate job separation rate decline. The shift-share decomposition would help to dictate how to model the decline in the aggregate job separation rate.



Figure 1: Aggregate job separation rate

Source: Monthly CPS (1983–2018).

Note: The solid line plots the monthly job separation rate (13-month moving average). The dashed line is the fitted quadratic trend.

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<sup>4</sup>I download the data from <http://www.nber.org/sipp/> and adapt the do files provided by CEPR (<https://ceprdata.org/sipp-uniform-data-extracts/sipp-extraction-programs/>) to clean the data. For the pre-1990 panels, I modify the CEPR-provided do files accordingly, which includes adjusting the sampling weights because the survey rollout is different for the pre-1990 panels.

### 2.2.1 Decline in the aggregate job separation rate

Figure 1 plots the declining aggregate job separation rate over time. This is the monthly job separation rate; it is the probability that a worker is employed this month and unemployed the next month. The decline in the aggregate job separation rate has been documented in the previous literature.

### 2.2.2 Employment shares have shifted towards more specific occupations that have lower job separation rates

In Figure 2, I fix the occupation specificity of each occupation at the JZ1977 and plot the employment shares by JZ1977 over time. For presentation purposes, the five job zones are aggregated into three levels: low ( $JZ = 1$ ), medium ( $JZ = 2$  or  $3$ ), and high ( $JZ = 4$  or  $5$ ). Employment shares have shifted from less specific occupations to more specific occupations.

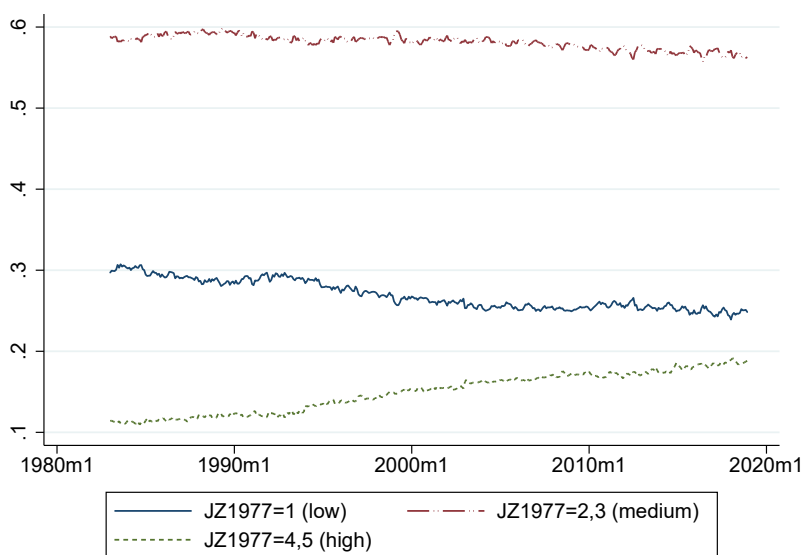


Figure 2: Employment shares by initial occupation specificity

Source: Monthly CPS (1983-2018), DOT/O\*NET.

Note: Figure 2 plots the share of employment by initial occupation specificity (fixed at 1977 job zone). By the definition of job zones (JZ) in the DOT/O\*NET of any time period, occupations are rated on a five-point scale with higher values representing higher occupation specificity (longer occupation-specific training). The five job zones are aggregated to three levels of occupation specificity (low ( $JZ = 1$ ), medium ( $JZ = 2$  or  $3$ ), and high ( $JZ = 4$  or  $5$ )) to reduce the number of groups. Occupations in low, medium, high job zones require an average length of 8, 12, and 24 weeks of occupation-specific training respectively.

The more specific occupations, towards which employment shares have shifted, have lower average job separation rates. This is shown in Figure 3. I fix the occupation specificity of each occupation at JZ1977 and plot over time the monthly average job separation rate by JZ1977. The monthly average job separation rate of a job zone this month is the probability that a worker employed this month in an occupation assigned the given job zone is unemployed the next month. The average job separation rate is lower for more specific occupations.





Figure 3: Job separation rates by initial occupation specificity

Source: Monthly CPS (1983–2018), DOT/O\*NET.

Note: Figure 3 plots the monthly job separation rate (13-month moving average) by initial occupation specificity (fixed at 1977 job zone). By the definition of job zones (JZ) in the DOT/O\*NET of any time period, occupations are rated on a five-point scale with higher values representing higher occupation specificity (longer occupation-specific training). The five job zones are aggregated to three levels of occupation specificity (low (JZ = 1), medium (JZ = 2 or 3), and high (JZ = 4 or 5)) to reduce the number of groups. Occupations in low, medium, high job zones require an average length of 8, 12, and 24 weeks of occupation-specific training respectively. The dotted lines are the fitted quadratic trends.

Figure 2 and Figure 3 suggest that one possible reason for the decrease in the aggregate job separation rate is the shift of employment shares towards more specific occupations with lower job separation rates (“between-group effect”).

### 2.2.3 Occupation specificity has increased within occupations

In Figure 4, I plot histograms of occupation specificity for the 338 occupations over time. The gray bars plot the distribution of occupation specificity as measured in the 1977 DOT (that is, JZ1977). The red bars plot the distribution of occupation specificity measured in 2017 from O\*NET (that is, JZ2017). The histogram shows that overall specificity has increased within occupations.<sup>5</sup>

<sup>5</sup>Examples of occupations that have become more specific over time are provided in the appendix.

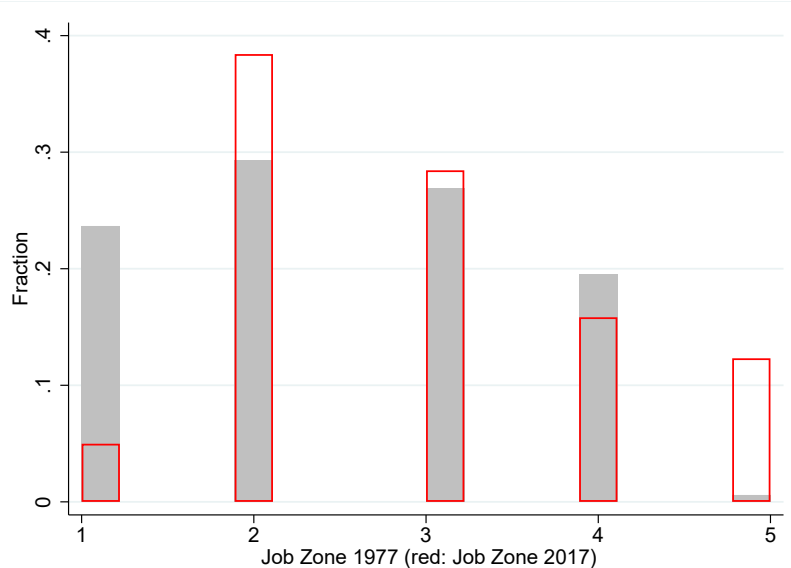


Figure 4: Shift in distribution of occupation specificity across occupations

Source: DOT/O\*NET.

Note: Figure 4 plots the histograms of occupation specificity for the 338 occupations, over time. By the definition of job zones (JZ) in the DOT/O\*NET of any time period, occupations are rated on a five-point scale with higher values representing higher occupation specificity (longer occupation-specific training). The gray bars plot JZ1977 (SVP rating from the 1977 DOT aggregated to the five job zones). The red bars plot JZ2017 (five job zones from the 2017 O\*NET).

Table 1: Transition matrix, change in occupation specificity

JZ1977 → JZ2017	1	2	3	4	5	Total
1	11 (0.1375)	58 (0.7250)	11 (0.0875)	0 (0.000)	0 (0.000)	80 (1.000)
2	1 (0.0101)	58 (0.5859)	30 (0.3030)	10 (0.1010)	0 (0.000)	99 (1.000)
3	1 (0.0110)	14 (0.1538)	44 (0.4835)	21 (0.2308)	11 (0.1209)	91 (1.000)
4	0 (0.000)	5 (0.0758)	9 (0.1364)	30 (0.4545)	22 (0.3333)	66 (1.000)
5	0 (0.000)	0 (0.000)	0 (0.000)	0 (0.000)	2 (1.000)	2 (1.000)
Total	57 (0.0385)	75 (0.3993)	89 (0.2781)	88 (0.1805)	29 (0.1036)	338 (1.000)

Source: DOT/O\*NET.

Note: By the definition of job zones (JZ) in the DOT/O\*NET of any time period, occupations are rated on a five-point scale with higher values representing higher occupation specificity (longer occupation-specific training). In Table 1, occupations are grouped by initial specificity JZ1977 and later specificity JZ2017. Each row contains occupations by the initial specificity JZ1977. In a given row, the columns show the number of occupations (underneath in the parentheses are the shares) assigned to each level of later occupation specificity measured by JZ2017.

Table 1 is a “transition matrix” showing the increase in occupation specificity within occupations. Occupations are grouped by initial specificity JZ1977 and later specificity JZ2017. Each row contains occupations by initial specificity JZ1977. At a given row, the columns show the number of occupations assigned to each level of later occupation specificity measured by JZ2017. In the parentheses are the relative percentages of the later specificity JZ2017 within each initial specificity JZ1977. Again, overall specificity has increased within occupations. For example, payroll clerks used to be nonspecific, assigned JZ1977 = 1, and their human capital was easily applicable to other occupations. Later, these occupations became more specific, assigned JZ2017 = 2, and the associated capital is more difficult to apply to other occupations.

From Figure 4 and Table 1, approximately half the occupations faced an increase in occupation specificity. This suggests that the decline in the aggregate job separation rate is due to the increase in specificity within occupations (“within-group effect”). If increasing occupation specificity lowers an occupation’s job separation rate, this would also reduce the aggregate job separation rate.

### 2.2.4 Shift-share decomposition of the decline in the aggregate job separation rate

I have documented two patterns in the data. One is that the employment shares have moved towards more specific occupations, which have lower job separation rates (“between-group effect”). The other is that within-occupation specificity has increased (“within-group effect”). Either observation can contribute to the decline in the aggregate job separation rate. The question is which of the two observations is the main driver of the decline in the aggregate job separation rate.

I first group occupations by their initial specificity (JZ1977) aggregated to three levels: low (JZ1977 = 1), medium (JZ1977 = 2 or 3), and high (JZ1977 = 4 or 5).<sup>6</sup> The aggregate job separation rate  $A_t$  is a share-weighted sum of job separation rates by each group

$$A_t = \sum w_{g,t} A_{g,t}$$

where  $w_{g,t}$  is the employment share for group  $g$  at month  $t$ , and  $A_{g,t}$  is the job separation rate for group  $g$  at month  $t$ .

The change in the aggregate job separation rate between months  $t$  and  $t - 1$  can be written as

$$\begin{aligned} \Delta A_t &= \sum w_{g,t} A_{g,t} - \sum w_{g,t-1} A_{g,t-1} \\ &= \underbrace{\sum_g A_{g,t-1} \Delta w_g}_{\text{between-group}} + \underbrace{\sum_g w_{g,t-1} \Delta A_g}_{\text{within-group}} + \underbrace{\sum_g \Delta w_g \Delta A_g}_{\text{covariance}} \end{aligned}$$

where  $\Delta A_t \equiv A_t - A_{t-1}$  is the change in the aggregate job separation rate between months  $t$  and  $t - 1$ ,  $\Delta A_g \equiv A_{g,t} - A_{g,t-1}$  is the change in the job separation rate of group  $g$  between months  $t$  and  $t - 1$ , and  $\Delta w_g \equiv w_{g,t} - w_{g,t-1}$  is the change in the employment share of group  $g$  between months  $t$  and  $t - 1$ .

<sup>6</sup>This is to maintain consistency with Figures 2 and 3, where average job separation rates and employment shares by occupation specificity were presented in terms of these three levels. The shift-share decomposition results using three levels (low, medium, high) are nearly identical to the results using the original five job zones as groups.

The first term  $\sum_g A_{g,t-1} \Delta w_g$ , the between-group effect, lets the weights change over time and fixes the group-specific job separation rates at the initial period  $t - 1$  level. The idea is that the shift of employment towards specific occupations (whose initial job separation rates are lower) reduces the aggregate job separation rate. The second term  $\sum_g w_{g,t-1} \Delta A_g$ , the within-group effect, fixes the weights at the initial period  $t - 1$  level and lets the group-specific job separation rates change over time. If increasing occupation specificity lowers an occupation’s job separation rate, such a decline in occupation-specific job separation rates due to increased occupation specificity also reduces the aggregate job separation rate. The third term  $\sum_g \Delta w_g \Delta A_g$  is the comovement of within-group changes and across-group changes.

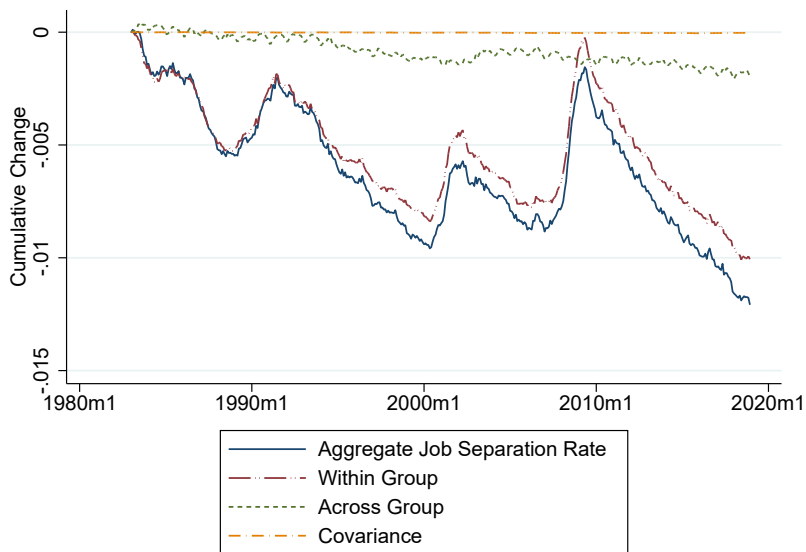


Figure 5: Shift-share decomposition based on initial specificity

Source: Monthly CPS (1983–2018), DOT/O\*NET.

Note: The monthly change in the aggregate job separation rate is decomposed into the between-group monthly change, within-group monthly change, and monthly covariance terms. The group in the shift-share decomposition is the occupations’ initial specificity JZ1977 (1977 SVP rating, aggregated to the five job zones, which are then grouped by three categories: low (JZ1977 = 1), medium (JZ1977 = 2 or 3), and high (JZ1977 = 4 or 5)). Figure 5 plots the cumulative sum of each of these monthly changes.

I compute the monthly change in the aggregate job separation rate, the between-group monthly change, the within-group monthly change, and the monthly covariance term for every pair of consecutive months during the sample period. In Figure 5, I plot the cumulative sum of each of these monthly changes. The aggregate job separation rate has decreased by around 1 percentage point (p.p.) over the CPS sample period (approximately 50% decrease). Almost all of this decline is from the “within-group effect.”

The shift-share decomposition results show that within-group changes in the job separation rate account for most of the aggregate job separation rate decline. The next question is within which particular group of occupations the decline in the job separation rate is concentrated.

I group occupations into three levels by their initial specificity (low (JZ1977 = 1), medium

Table 2: Group accounting for the decline in the aggregate job separation rate

Group		$w_g \Delta A_g$
JZ1977 = low	→ JZ2017 = medium	-0.004
JZ1977 = medium	→ JZ2017 = medium	-0.004
JZ1977 = low	→ JZ2017 = low	-0.001
JZ1977 = medium	→ JZ2017 = low	-0.001
JZ1977 = medium	→ JZ2017 = high	-0.000
JZ1977 = high	→ JZ2017 = high	-0.000
JZ1977 = high	→ JZ2017 = medium	-0.000

Source: Monthly CPS (1983–2018), DOT/O\*NET.

Note: By the definition of job zones (JZ) in the DOT/O\*NET of any time period, occupations are rated on a five-point scale with higher values representing higher occupation specificity (longer occupation-specific training). The five job zones are aggregated to three levels of occupation specificity (low (JZ = 1), medium (JZ = 2 or 3), and high (JZ = 4 or 5)) to reduce the number of groups. Occupations in low, medium, high job zones require an average length of 8, 12, and 24 weeks of occupation-specific training respectively.

I group occupations by their initial specificity and whether their specificity increased/remained the same/decreased at the end of the sample period (JZ1977 in 1983 vs. JZ2017 in 2018). I compute for each group the product of its initial employment share  $\times$  cumulative change in the job separation rate as the end of the sample period. Table 2 lists the results in descending order.

(JZ1977 = 2 or 3), and high (JZ1977 = 4 or 5)) and whether their specificity increased/remained the same/decreased at the end of the CPS sample period (for a total of seven groups). I compute for each group the product of its initial employment share  $\times$  cumulative change in its job separation rate. Table 2 lists the results in descending order. It turns out that the group of occupations that were initially not specific and have become more specific (JZ1977 = low in 1983  $\rightarrow$  JZ2017 = medium in 2018)<sup>7</sup> over time contributes the most (first row in Table 2) to the decline in the aggregate job separation rate.

To visualize the contribution of this group of occupations that were initially not specific and have become more specific, I plot in Figure 6 the “counterfactual” aggregate job separation rate and compare it to the actual aggregate job separation rate. The actual aggregate job separation rate is a weighted sum of the group-specific job separation rates weighted by the employment shares of each group. The counterfactual aggregate job separation rate is obtained by fixing only the job separation rate of the group of occupations that were initially not specific and have become more specific over time at its initial level. This group accounts for half the observed decline in the aggregate job separation rate.

In short, according to the shift-share decomposition, most of the decline in the aggregate job separation rate can be attributed to the increase in specificity within occupations. Furthermore, the largest contributor to the decline in the aggregate job separation rate is the group of occupations

<sup>7</sup>Because the occupation specificity measure is not available for all periods pre-2000, I assign JZ1977 to years 1983–1985, JZ1991 to years 1986–1995, and JZ2000 1995–2000. After 2000, when job zone data are available each year, the corresponding job zone is assigned to that year (JZ2017 is assigned for 2018).

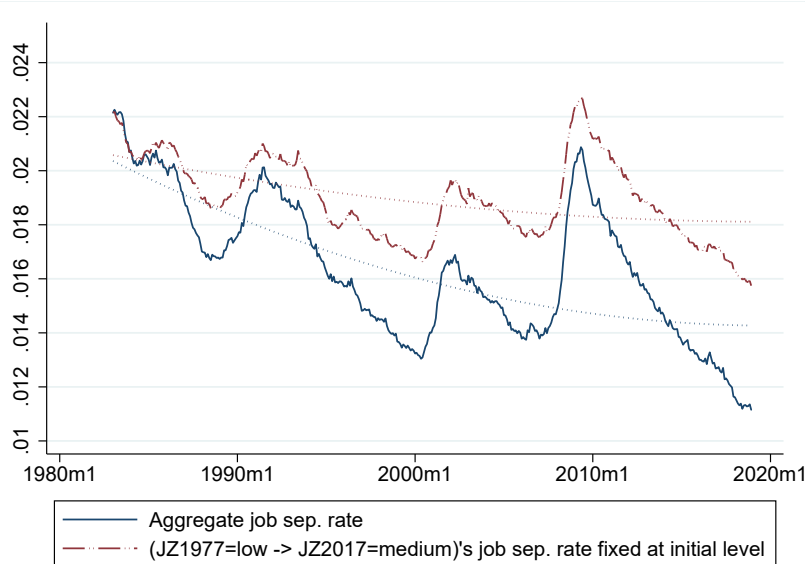


Figure 6: Counterfactual vs. observed aggregate job separation rate

Source: Monthly CPS (1983–2018), DOT/O\*NET.

Note: Figure 6 plots the “counterfactual” aggregate job separation rate and compares it to the observed aggregate job separation rate. By the definition of job zones (JZ) in the DOT/O\*NET of any time period, occupations are rated on a five-point scale with higher values representing higher occupation specificity (longer occupation-specific training). The five job zones are aggregated to three levels of occupation specificity (low (JZ = 1), medium (JZ = 2 or 3), and high (JZ = 4 or 5)) to reduce the number of groups. Occupations in low, medium, high job zones require an average length of 8, 12, and 24 weeks of occupation-specific training respectively.

The “counterfactual” aggregate job separation rate is obtained by fixing only the job separation rate of the group of occupations that were initially not specific and have become more specific over time (initially JZ1977 = low in 1983 → JZ2017 = medium in 2018) at its initial level. The dotted blue line is the quadratic trend of the observed aggregate job separation rate (solid blue line), and the dotted red line is the quadratic trend of the “counterfactual” aggregate job separation rate (dashed red line).

that were initially nonspecific and have become more specific over time. The following section provides more direct evidence that the increase in specificity within occupations has a decreasing effect on the job separation rate.

### 2.3 Decreasing effect of the increase in occupation specificity on the job separation rate

I run a regression using the monthly CPS (1983–2018) to estimate the effect of increasing occupation specificity on the job separation rate. Each month I collect the following information from employed workers: the indicator  $\mathbb{I}\{EU\}$ , which is 1 if the worker is unemployed the next month and 0 if still employed the next month, the initial specificity (denoted as  $JZ_{1977}$ ) and the contemporary specificity (denoted as  $JZ_{new}$ ) of the worker’s current occupation this month. As before, to reduce the number of groups, the five job zones are aggregated to three levels of occupation specificity (low (JZ = 1), medium (JZ = 2 or 3), and high (JZ = 4 or 5)).<sup>8</sup>

<sup>8</sup>The regression results using the original five levels of occupation specificity are provided in the appendix. The result that increasing occupation specificity depresses the job separation rate remains.

I regress  $\mathbb{I}\{EU\}$  on the set of indicator variables that combine two pieces of information. One is the initial specificity ( $JZ1977$ ) of the currently held occupation. The second is whether the contemporary specificity ( $JZnew$ ) of this current occupation is higher or lower than its initial specificity.

The purpose of Regression (1) is to test whether increasing (decreasing) occupation specificity has a decreasing (increasing) effect on the job separation rate. In Regression (1), the coefficients in front of  $\mathbb{I}\{JZ1977 = j\}$  correspond to the average job separation rate of occupations whose occupation specificity has not changed ( $JZnew$  is the same as  $JZ1977$ ). If the hypothesis holds, compared to this job separation rate of occupations whose specificity has not changed, the job separation rate of occupations that have become more specific ( $JZnew$  is larger than  $JZ1977$ ) should be lower. That is, the coefficients in front of  $\mathbb{I}\{JZ1977 = low, JZnew = medium\}$  or  $\mathbb{I}\{JZ1977 = medium, JZnew = high\}$  are predicted to be negative. Likewise, the job separation rate of occupations that have become less specific should be higher; the coefficients in front of  $\mathbb{I}\{JZ1977 = medium, JZnew = low\}$  or  $\mathbb{I}\{JZ1977 = high, JZnew = medium\}$  are predicted to be positive.

$$\begin{aligned} \mathbb{I}\{EU_{it}\} = & \alpha_{low,same} \mathbb{I}\{JZ1977_{it} = low\} + \alpha_{low,increase} \mathbb{I}\{JZ1977_{it} = low, JZnew_{it} = medium\} \\ & + \alpha_{medium,same} \mathbb{I}\{JZ1977_{it} = medium, JZnew_{it} = medium\}_{it} \\ & + \alpha_{medium,increase} \mathbb{I}\{JZ1977_{it} = medium, JZnew_{it} = high\} \\ & + \alpha_{medium,decrease} \mathbb{I}\{JZ1977_{it} = medium, JZnew_{it} = low\} \\ & + \alpha_{high,same} \mathbb{I}\{JZ1977_{it} = high\} + \alpha_{high,decrease} \mathbb{I}\{JZ1977_{it} = high, JZnew_{it} = medium\} + \epsilon_{it} \end{aligned}$$

Table 3 reports the regression results. Column 1 contains the baseline result. One observation is that occupations that are more specific, measured by initial specificity  $JZ1977$ , have lower average job separations rates. This corresponds to the first observation from Figure 3 that plots the monthly job separation rates over time by  $JZ1977$ . The other observation is that given any level of  $JZ1977$ , occupations that have become more specific have lower job separation rates than occupations whose specificity has remained the same. This is confirmed by the negative coefficient estimates in front of  $\mathbb{I}\{JZ1977 = low, JZnew = medium\}$  or  $\mathbb{I}\{JZ1977 = medium, JZnew = high\}$ . For example, the average job separation of occupations that were initially nonspecific and have remained nonspecific ( $JZ1977 = low, JZnew = low$ ) is 2.589%. The average job separation rate of occupations that have become more specific after being initially nonspecific ( $JZ1977 = low, JZnew = medium$ ) is lower by 0.510 p.p., equal to  $2.589 - 0.510 = 2.079\%$ .

The regression in Column 2 controls for workers' sex, race, marital status, age, and years of general education. Adding worker controls addresses the possibility that occupations that have become more specific consist of different types of workers, which in turn affects their average job separation rate. The results are robust to the introduction of these controls.

Table 3: Decreasing effect of the increase in occupation specificity on the job separation rate

	(1)	(2)
	$\mathbb{I}\{EU\} \times 100$	$\mathbb{I}\{EU\} \times 100$
$\mathbb{I}\{JZ1977 = low\}$	2.589*** (0.014)	5.564*** (0.037)
$\mathbb{I}\{JZ1977 = low, JZnew = medium\}$	-0.510*** (0.019)	-0.402*** (0.019)
$\mathbb{I}\{JZ1977 = medium\}$	1.381*** (0.006)	4.678*** (0.036)
$\mathbb{I}\{JZ1977 = medium, JZnew = high\}$	-0.572*** (0.010)	-0.265*** (0.010)
$\mathbb{I}\{JZ1977 = medium, JZnew = low\}$	0.626*** (0.027)	0.364*** (0.027)
$\mathbb{I}\{JZ1977 = high\}$	0.638*** (0.008)	4.389*** (0.040)
$\mathbb{I}\{JZ1977 = high, JZnew = medium\}$	0.766*** (0.020)	0.451*** (0.020)
Controls	No	Yes
$N$	12299863	12299863

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Source: Monthly CPS (1983–2018), DOT/O\*NET.

Note: By the definition of job zones (JZ) in the DOT/O\*NET of any time period, occupations are rated on a five-point scale with higher values representing higher occupation specificity (longer occupation-specific training). To reduce the number of groups, the five job zones are aggregated to three levels of occupation specificity (low (JZ = 1), medium (JZ = 2 or 3), and high (JZ = 4 or 5)). Occupations in low, medium, high job zones require an average length of 8, 12, and 24 weeks of occupation-specific training respectively.

Regressions (1) and (2) regress  $\mathbb{I}\{EU\}$ , the indicator that the worker is employed this month and unemployed the next month, on the set of indicator variables marking the initial occupation specificity  $JZ1977$  of the current occupation, and whether the contemporaneous specificity  $JZnew$  of this current occupation is higher or lower than its initial occupation specificity.

Regression (2) adds controls: education, age, sex, marital status, race of the worker. Standard errors are in parentheses. Basic monthly weights are used in all regressions.



### 3 Model

The shift-share decomposition and regression results motivate a model where the increase in occupation-specific training within occupations reduces job separations. Furthermore, the largest contributor to the aggregate job separation rate decline is the group of occupations that were initially nonspecific and have become more specific over time (which is a subgroup of the working population). Therefore, I build a search-and-matching model to learn why the increase in specificity within occupations reduces job separations. I calibrate the initial steady state of the model to match the job separation rate of the initially nonspecific group of occupations at the beginning of the CPS sample period. The outcomes by which the model is evaluated would be (i) how much the job separation rate of the initially nonspecific group of occupations declines over the time after they become more specific, (ii) the job separation rates of the rest of the population, the initially specific occupations, before and after they become even more specific, (iii) how much the aggregate job separation rate declines, and (iv) how much of the decline in the aggregate job separation can be accounted for by this group.

The model section is organized as follows. Section 3.1 provides a preview of the model, experiments conducted with the model and the model’s mechanism. Then the following sections discuss the model and results in more detail. Sections 3.2 and 3.3 present the model equations, Section 3.4 calibrates the initial steady state of the model, Section 3.5 conducts the experiments, Section 3.6 discusses the model’s mechanism, and Section 3.7 evaluates the model’s performance in predicting the decline in the aggregate job separation rate.

#### 3.1 Preview

##### Summary of model and assumptions

The model characterizes the labor market of workers and firms in a finite number of occupations all in one same job zone; all the occupations have the same level of occupation specificity. Two parameters in the model define occupation specificity. One is the output gap  $\tau$  by which nontrained workers are less productive than trained workers due to the lack of occupation-specific human capital. The other is the exogenous probability  $\mu$  each period during employment that nontrained workers become trained workers by acquiring the occupation-specific human capital. Its inverse  $1/\mu$  would be the average length of occupation-specific training, assumed to take place during employment only. Later, when experimenting with the model to see the effects of increasing occupation specificity, the output gap  $\tau$  and the average length of occupation-specific training  $1/\mu$  will be increased. The increase in the output gap  $\tau$  can be interpreted as the increase in the amount of occupation-specific human capital required to become trained due to, for example, advances in occupation-specific technology. The increase in  $1/\mu$  means that it takes a longer time to acquire the occupation-specific capital.

Employed workers’ output is the product of both their occupation-specific human capital and idiosyncratic productivity  $z$ . Idiosyncratic productivity  $z \sim F(z_{t+1}|z_t)$  follows a first-order Markov

process. It is general in that it is persistently retained (via the Markov process) regardless of whether the worker is employed or unemployed or whether the worker switches occupation. An employed trained worker with idiosyncratic productivity  $z$  produces output  $z$ , while an employed nontrained worker with  $z$  produces output  $(1 - \tau)z$ . Nontrained workers are less productive than trained workers (hence an output gap  $\tau$ ) due to the absence of occupation-specific human capital. While employed, nontrained workers are subject to the exogenous probability  $\mu$  each period to become trained workers. It is assumed that this occupation-specific training takes place only during employment.<sup>9</sup> Both trained and nontrained workers can be separated from their job if their newly drawn idiosyncratic productivity is too low to sustain the job. Job separations are transitions from employment to unemployment only; the model abstracts from job-to-job transitions.

At the beginning of each period, unemployed workers are subject to an exogenous probability of occupation switching. It is assumed that occupation switching occurs with an exogenous probability<sup>10</sup> and occurs during unemployment only. If hit by the occupation-switching shock, unemployed trained workers lose their occupation-specific capital from the previous occupation and become nontrained workers seeking employment in the new occupation. In the event of an occupation switch, unemployed workers are randomly assigned with equal probability to any other (symmetric) occupation and seek employment in the new occupation.<sup>11</sup> It is also assumed that occupation switching occurs between (symmetric) occupations within the same job zone only. In other words, job zones (which are groups of occupations of the same occupation specificity) are assumed to be isolated labor markets; there is no movement of workers between different job zones. Unemployed workers who are hit by the occupation-switching shock are assumed to stay unemployed in the new occupation for the rest of the period; they cannot immediately meet potential employers and become employed in the new occupation by the end of the same period. Unemployed workers who are not hit by the occupation-switching shock maintain their trained or nontrained status while seeking employment in the same occupation, and they could possibly meet potential employers and become employed in the same occupation by the end of the same period.

The labor market is segmented by occupation  $o$ , trained ( $NT$ ) or nontrained ( $NT$ ) worker status, and idiosyncratic productivity  $z$ . Frictions prevent the instantaneous matching of unemployed workers to vacant jobs. The number of matches of unemployed workers to vacant jobs is determined by the same constant-returns-to-scale (CRS) matching function in any submarket. To ensure job finding rates are between 0 and 1, the CRS matching function is assumed to be  $m(u, v) = uv/[u^\eta + v^\eta]^{1/\eta}$ . In any submarket, the probability of an unemployed worker being matched to a job is

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<sup>9</sup>In reality, unemployed people also seek occupation-specific training.

<sup>10</sup>In the companion paper, I relax this assumption and endogenize occupation switching. Hence workers choose whether to switch occupations as well as choose whether to separate from their job.

<sup>11</sup>Occupations switching is assumed to occur during unemployment because the focus of this paper is the role of the increasing loss of occupation-specific capital experienced by occupation switchers when occupations require more occupation-specific training. Such loss of occupation-specific capital is likely to occur when workers switch occupations after an unemployment spell. On the other hand, occupation switching without an intervening unemployment spell (job-to-job transition) is more likely a career progression. On a related note, occupations are assumed to be symmetric because it suffices to have workers lose occupation-specific human capital when they switch occupations; it does not matter between which particular occupations they are switching.

$f(\theta) \equiv m/u = \theta/[1 + \theta^\eta]^{1/\eta}$ , where  $\theta \equiv v/u$  is the vacancy-to-unemployment ratio or market tightness.  $f(\theta)$  is increasing in  $\theta$ . The probability that a vacancy is matched to an unemployed worker is  $q(\theta) \equiv m/v = 1/[1 + \theta^\eta]^{1/\eta}$ , which is decreasing in  $\theta$ .

Time subscripts are omitted in the value functions presented below, and the next period is labeled with a prime. Superscripts with  $NT$  indicate the function or parameter is for the nontrained type. Superscripts with  $T$  indicate the function or parameter is for the trained-type. Moreover, because occupations are symmetric, without loss of generality, the index  $o$  for occupation can be dropped from the value functions.

### Calibration of initial steady state and experiments conducted

The model is calibrated so that the initial steady state matches the labor market of nonspecific occupations (JZ1977 = low) at the beginning of the CPS sample period, in particular their 3% job separation rate.<sup>12</sup> This is motivated by my empirical finding from Section 2.2 that the group of occupations that were initially nonspecific and have become more specific over time (as opposed to the occupations that were already specific at the start of the sample period) contributes the most to the decline in the aggregate job separation rate. After the initial steady state is calibrated, the model is asked to predict the decline in job separation rates by initial specificity (JZ1977 = low, medium, high) after (all the) occupations become more specific. These job separation rates are each obtained by simulating the same model after increasing the values of the two occupation specificity parameters (average length of occupation-specific training  $1/\mu$  and output gap  $\tau$ ) accordingly, keeping the remaining parameters at their initial steady-state values. The model's predicted job separation rates (by initial specificity) will be compared with the data. Then these job separation rates are aggregated, using employment shares by occupation specificity at the beginning of the sample period from the CPS, to also obtain the model's prediction on the decline in the aggregate job separation rate.<sup>13</sup> The model will also be evaluated by whether it can match my empirical finding that the group of occupations that were initially nonspecific and have become more specific plays the largest role in reducing the aggregate job separation rate.

The increase in occupation specificity in the model must match the increase in occupation specificity in the data. The occupation specificity parameters in the model are (i) the average length of time  $1/\mu$  that it takes for nontrained workers to obtain the occupation-specific human capital and become trained workers in the occupation and (ii) the output gap  $\tau$  by which nontrained workers are less productive because they do not have the occupation-specific human capital. The increase in  $1/\mu$

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<sup>12</sup>By the definition of job zones (JZ) in the DOT/O\*NET of any time period, occupations are rated on a five-point scale with higher values representing higher occupation specificity (longer occupation-specific training). To reduce the number of groups, the five job zones are aggregated to three levels of occupation specificity (low (JZ = 1), medium (JZ = 2 or 3), and high (JZ = 4 or 5)).

<sup>13</sup>The model has no say about changes in employment shares across different job zones because job zones are assumed to be isolated labor markets. This model setup is motivated by my shift-share decomposition result from Section 2.2 that shifts in employment shares across job zones do not contribute much to the decline in the aggregate job separation rate. Therefore, shares are fixed, using shares at the beginning of the sample period brought externally from the CPS.

is informed by the definition of job zones in the DOT/O\*NET, which lists groups of occupations with the same length of required occupation-specific training. The increase in  $\tau$  is informed by regression estimates I obtain from the SIPP (1985–2013) on the increase in the relative wage losses faced by workers who switch occupations after an unemployment spell (relative to non-occupation switchers) when their previously held occupation becomes more specific. The wage penalty associated with occupation switching increases when the previous occupation becomes more specific because less of the previous human capital is carried over to the new occupation. Details on calibrating the occupation specificity parameters are presented in the appendix.

## Mechanism

The decline in the aggregate job separation rate from increasing occupation specificity is primarily driven by the decline in job separations by trained workers who have occupation-specific human capital. In the model, occupations becoming more specific means an increase in the output gap  $\tau$  between nontrained and trained workers or the average length of occupation-specific training time  $1/\mu$ . Under either definition of increasing occupation specificity, trained workers become more reluctant to separate from their job. Suppose a trained worker becomes unemployed and is then hit by the exogenous occupation-switching shock, causing this worker to become a nontrained worker in a different occupation. A larger output gap (longer period of occupation-specific training) means a larger gap in occupation-specific capital that this worker must catch up on (a longer period of occupation-specific training that this worker must undergo) while earning lower wages as a nontrained worker. Hence trained workers are less motivated to separate from their current job to avoid the future possibility of having to switch occupations.<sup>14</sup> The model implies that following the increase in occupation specificity, trained workers are willing to accept lower wages at their current job at the same level of productivity to avoid job separation. The model implies that following the increase in occupation specificity, trained workers are willing to accept lower wages at their current job at the same level of productivity to avoid job separation.

## 3.2 Value functions of workers and firms

The value function of an unemployed worker who is trained in occupation  $o$  with idiosyncratic productivity  $z$  is

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<sup>14</sup>In the companion paper, I endogenize occupation switching. In this case, the incentive for trained workers to not separate from their job to avoid unwanted occupation switching lessens. Here workers choose whether or not to switch occupations, thereby disentangling the choice to switch occupations from the choice to separate from their job. Under endogenous occupation switching, trained workers remain attached to their previous occupation after becoming unemployed, lengthening unemployment spells.

$$\begin{aligned}
U^T(z) &= b + \beta(1 - \lambda)(1 - f(\theta^T(z)))\mathbb{E}_{z'|z} [U^T(z')] \\
&\quad + \beta(1 - \lambda)f(\theta^T(z))\mathbb{E}_{z'|z} [\max \{W^T(z'), U^T(z')\}] \\
&\quad + \beta\lambda\mathbb{E}_{z'|z} [U^{NT}(z')]
\end{aligned} \tag{3.1}$$

where  $b$  is the value of unemployment,  $\beta$  is the discount factor,  $\lambda$  is the exogenous probability of switching occupation. The expectation  $\mathbb{E}_{z'|z}$  reflects the uncertainty around next period's idiosyncratic productivity  $z'$  conditioning on current  $z$ . The case of no occupation switch has three possible outcomes. Unemployed workers may not be matched to a job and remain unemployed. They may be matched to a potential job but realize a too-low productivity and hence become unemployed again ( $W < U$ ). They may be potentially matched and realize a high enough productivity and become employed ( $W > U$ ) as a trained worker next period in the same occupation. The max operator reflects these two cases of endogenous match rejection/acceptance. In the case of an occupation switch, they become unemployed as nontrained workers in a different (symmetric) occupation. A trained worker's previous occupation-specific human capital is not applicable to the new occupation. It is also assumed that after switching occupations, workers remain unemployed and cannot meet any potential employer until the end of the period.

The value function of an unemployed worker who is nontrained in occupation  $o$  with idiosyncratic productivity  $z$  is

$$\begin{aligned}
U^{NT}(z) &= b + \beta(1 - \lambda)(1 - f(\theta^{NT}(z)))\mathbb{E}_{z'|z} [U^{NT}(z')] \\
&\quad + \beta(1 - \lambda)f(\theta^{NT}(z))\mathbb{E}_{z'|z} [\max \{W^{NT}(z'), U^{NT}(z')\}] \\
&\quad + \beta\lambda\mathbb{E}_{z'|z} [U^{NT}(z')]
\end{aligned} \tag{3.2}$$

The value of being a nontrained unemployed worker depends on  $b$ . It also depends on (i) in the case of no occupation switch, the discounted value of remaining unemployed  $U$  or having a job  $W$  as a nontrained worker in the next period in the same occupation, and (ii) in the case of an occupation switch, the discounted value of being an unemployed nontrained worker in a different (symmetric) occupation. Again, it is assumed that workers cannot meet any potential employer after switching occupations until the end of the period.

The value function of a trained worker in occupation  $o$  with idiosyncratic productivity  $z$  is

$$\begin{aligned}
W^T(z) &= wage^T(z) + \beta(1 - \delta)\mathbb{E}_{z'|z} [\max \{W^T(z'), U^T(z')\}] \\
&\quad + \beta\delta\mathbb{E}_{z'|z} [U^T(z')]
\end{aligned} \tag{3.3}$$

where  $wage^T(z)$  is the wage. There is exogenous match separation probability  $\delta$ . The max operator

reflects endogenous match separation. Whenever the value of employment  $W$  is lower than the value of being unemployed  $U$ , the worker will separate and receive the value  $U$  next period.

The value function of a nontrained worker in occupation  $o$  with idiosyncratic productivity  $z$  is

$$\begin{aligned} W^{NT}(z) = & \text{wage}^{NT}(z) + \beta(1 - \delta)\mu\mathbb{E}_{z'|z} [\max \{W^T(z'), U^T(z')\}] \\ & + \beta(1 - \delta)(1 - \mu)\mathbb{E}_{z'|z} [\max \{W^{NT}(z'), U^{NT}(z')\}] + \beta\delta\mathbb{E}_{z'|z} [U^{NT}(z')] \end{aligned} \quad (3.4)$$

where  $\text{wage}^{NT}(z)$  is the wage. There is exogenous match separation probability  $\delta$ . Surviving an exogenous match separation has two possible outcomes. The nontrained worker becomes trained in this occupation with probability  $\mu$  (acquires the occupation-specific capital) or remains nontrained with probability  $1 - \mu$ . In either case, the max operator reflects endogenous match separation. Whenever the value of employment  $W$  is lower than the value of being unemployed  $U$ , the worker will separate and receive the value  $U$  next period.

The value function of a job filled with a worker trained in occupation  $o$  with idiosyncratic productivity  $z$  is

$$J^T(z) = z - \text{wage}^T(z) + \beta(1 - \delta)\mathbb{E}_{z'|z} [\max \{J^T(z'), V^T(z')\}] + \beta\delta\mathbb{E}_{z'|z} [V^T(z')] \quad (3.5)$$

where  $z$  is the output from the match, and  $\text{wage}^T(z)$  is the wage. There is an exogenous match separation probability  $\delta$ . If the exogenous match separation is survived, whenever the value of the filled job  $J$  is lower than the value of the vacancy  $V$ , the firm will endogenously separate and receive the value  $V$  next period.

The value function of a job filled with a worker nontrained in occupation  $o$  with idiosyncratic productivity  $z$  is

$$\begin{aligned} J^{NT}(z) = & (1 - \tau)z - \text{wage}^{NT}(z) + \beta(1 - \delta)\mu\mathbb{E}_{z'|z} [\max \{J^T(z'), V^T(z')\}] \\ & + \beta(1 - \delta)(1 - \mu)\mathbb{E}_{z'|z} [\max \{J^{NT}(z'), V^{NT}(z')\}] \\ & + \beta\delta\mathbb{E}_{z'|z} [V^{NT}(z')] \end{aligned} \quad (3.6)$$

where  $(1 - \tau)z$  is the output from the match, and  $\text{wage}^{NT}(z)$  is the wage.  $(1 - \tau)$  reflects that this nontrained worker is less productive due to the absence of occupation-specific capital. There is exogenous match separation probability  $\delta$ . Surviving an exogenous match separation has two possible outcomes. The nontrained worker becomes trained with probability  $\mu$  or remains nontrained with probability  $1 - \mu$ . In either case, the max operator reflects endogenous match separation. Whenever the value of the filled job  $J$  is lower than the value of the vacancy  $V$ , the firm will endogenously separate and receive the value  $V$  next period.

The values of a vacancy of a firm searching for a nontrained worker or a trained worker with

idiosyncratic productivity  $z$  in occupation  $o$  are

$$V^{NT}(z) = -k + \beta(1 - q(\theta^{NT}(z)))\mathbb{E}_{z'|z} [V^{NT}(z')] + \beta(q(\theta^{NT}(z)))\mathbb{E}_{z'|z} [J^{NT}(z')] \quad (3.7)$$

$$V^T(z) = -k + \beta(1 - q(\theta^T(z)))\mathbb{E}_{z'|z} [V^T(z')] + \beta(q(\theta^T(z)))\mathbb{E}_{z'|z} [J^T(z')] \quad (3.8)$$

The value of the vacancy depends on the vacancy posting cost  $k$  and the discounted value of remaining unfilled  $V$  or being filled  $J$  next period.

By free entry,

$$V^{NT}(z) = 0 \quad (3.9)$$

$$V^T(z) = 0 \quad (3.10)$$

Wages are determined to satisfy the standard Nash-bargaining solution:

$$wage^{NT}(z) = \arg \max_{wage} \left[ (W^{NT}(z) - U^{NT}(z))^\alpha (J^{NT}(z) - V^{NT}(z))^{1-\alpha} \right] \quad (3.11)$$

$$wage^T(z) = \arg \max_{wage} \left[ (W^T(z) - U^T(z))^\alpha (J^T(z) - V^T(z))^{1-\alpha} \right] \quad (3.12)$$

where  $\alpha$  is the bargaining share of the worker.

Workers' idiosyncratic productivity evolves according to a mean zero AR(1) process  $\log z_t = \rho_z \log z_{t-1} + e_{zt}$ , where  $e_{zt} \sim N(0, \sigma_z^2)$ .

### 3.3 Equilibrium

Equations (3.1)–(3.12) are solved for each type  $i = NT, T$ , market tightness  $\theta^i(z)$ ,  $wage^i(z)$ , value functions  $U^i(z)$ ,  $W^i(z)$ ,  $J^i(z)$ , reservation level  $z^{sep,i}$  for productivity  $z$  below which workers and firms endogenously choose to separate, given values for vacancy posting cost  $k$ , discount factor  $\beta$ , exogenous separation probability  $\delta$ , exogenous occupation switching probability  $\lambda$ , output gap  $\tau$  between trained and nontrained workers, value of unemployment  $b$ , exogenous probability  $\mu$  that a nontrained worker in an occupation becomes a trained worker, parameters  $\rho_z$  and  $\sigma_z$  governing the AR(1) process for  $z$ , worker's bargaining share  $\alpha$ , and matching function parameter  $\eta$ .

### 3.4 Calibration of initial steady state

The model has eleven parameters. The parameters values are set so that the model's initial steady state characterizes JZ1977 = low occupations at the beginning of the CPS sample period. This

calibration of the initial state is motivated by the empirical finding that the largest contributor to the decline in the aggregate job separation rate is the group of occupations that were initially nonspecific and have become more specific over time. Experiments are conducted later in Section 3.5 to see the effect of increasing occupation specificity parameters  $\tau$  and  $1/\mu$  on the job separation rate, relative to its initial steady state as nonspecific ( $JZ1977 = \text{low}$ ) occupations at the beginning of the CPS sample period.

Four parameters  $\beta$ ,  $\delta$ ,  $\alpha$ , and  $\mu$  are exogenously assigned values first without solving the model. The values of the other seven parameters  $\rho_z$ ,  $\sigma_z$ ,  $\tau$ ,  $b$ ,  $\lambda$ ,  $k$ , and  $\eta$  are determined internally so that these seven parameters along with the four exogenous parameters minimize the distance (the sum of log absolute differences) between the seven moments produced by the model and the target data moments.

Table 4: Parameter values for initial steady state

Exogenously assigned		Source
$\beta$ , discount factor, weekly	0.999	Annual interest rate 4%
$\delta$ , exogenous separation rate, weekly	0.001	JOLTS, Cairó and Cajner (2018)
$\alpha$ , worker’s bargaining share	0.500	den Haan et al. (2000)
$\mu$ , probability of becoming trained in occupation, weekly	1/8	DOT/O*NET
Endogenously chosen		
$\rho_z$ , persistence of worker idiosyncratic productivity $z$	0.986	Target data moments in Table 5
$\sigma_z$ , standard deviation of worker idiosyncratic productivity $z$	0.032	
$\tau$ , output gap between nontrained and trained workers	0.000	
$b$ , value of unemployment	0.828	
$k$ , vacancy posting cost	0.010	
$\eta$ , matching function parameter	5.204	
$\lambda$ , exogenous occupation-switching probability	0.080	

### 3.4.1 Parameters assigned externally

The model’s time frequency is weekly. The values for  $\beta$ ,  $\delta$ ,  $\alpha$ , and  $\mu$  are set exogenously. In the model simulation, workers “die” after an average of 40 years. “Newly born” workers are unemployed and nontrained and are randomly assigned occupations and idiosyncratic productivities. The discount factor  $\beta = (1 - d)/(1 + r)$  where the death probability,  $d$ , matches an average life of 40 years, and  $r$  matches an annual real interest rate of 4%, following the previous literature. Following Cairó and Cajner (2018), the exogenous job separation rate  $\delta$  is set to be one-third of the average monthly job separation rate 2% observed in the CPS. Cairó and Cajner (2018) refer to the Job Openings and Labor Turnover Survey (JOLTS) data, available from December 2000, where the average monthly separation rate due to layoffs is about 1.5%. Layoffs in JOLTS data correspond to separations



initiated by the employer and are interpreted as endogenous separations. Following the previous literature such as den Haan et al. (2000), the worker’s bargaining share  $\alpha$  is set to be 0.5. The average length of occupation-specific training  $1/\mu$  is equal to 8 (weeks), following the definition of nonspecific ( $JZ = \text{low}$ ) occupations in the DOT/O\*NET.

### 3.4.2 Parameters determined internally

The parameter values for  $\rho_z$ ,  $\sigma_z$ ,  $\tau$ ,  $b$ ,  $k$ ,  $\eta$ , and  $\lambda$  are jointly chosen to match seven data moments characterizing nonspecific ( $JZ1977 = \text{low}$ ) occupations at the beginning of the CPS sample period. They are chosen to minimize the sum of log absolute differences between the model moments and target data moments. However, the parameters differ in terms of the moments they primarily inform.

$\rho_z$  and  $\sigma_z$ , the persistence and standard deviation of workers’ idiosyncratic productivity, affect the wage penalty faced by non-occupation switchers, the wage penalty faced by occupation switchers, the job separation rate, and the job finding rate. Higher  $\rho_z$  and lower  $\sigma_z$  have a decreasing effect on the wage change after an unemployment spell (after wage minus before wage) faced by non-occupation and occupation switchers. Higher  $\rho_z$  increases the job separation rate because future idiosyncratic productivity is less likely to be better (idiosyncratic productivity does not mean-revert and hence improve quickly). Similarly, higher  $\rho_z$  reduces the job finding rate because it becomes less likely for workers to exceed the match formation cutoff. Higher  $\sigma_z$  increases the job separation rate because it becomes more likely for workers to fall below the separation cutoff. Likewise, higher  $\sigma_z$  reduces the job finding rate because workers are more likely to fall below the match formation cutoff.

The output gap  $\tau$  (by which nontrained workers are less productive due to the absence of occupation-specific capital) affects the wage penalty faced by occupation switchers, the job separation rate, and the job finding rate. A higher  $\tau$  increases the wage penalty faced by occupation switchers, in particular, the trained workers who lose their previous occupation-specific capital. A higher  $\tau$  reduces the job separation rate, as trained workers become more reluctant to separate because of the future possibility of the exogenous occupation-switching shock that occurs during unemployment. It also reduces the job finding rate because firms recruit less nontrained workers, who are less productive by the higher  $\tau$ .

A higher value of unemployment  $b$  increases the replacement ratio (value of unemployment  $b$ ’s share of the average wage). Also, higher  $b$  increases the job separation rate and reduces the job finding rate.

The remaining parameter values are determined as follows. Vacancy posting cost  $k$  is adjusted to produce the average market tightness of 0.5. Then the matching function parameter  $\eta$  is chosen so that given market tightness of 0.5, the job finding rate of 20% is obtained. Meanwhile  $\lambda$ , the exogenous probability of the occupation-switching shock that hits during unemployment, is adjusted to match the average 60% share of unemployment spells that end in an occupation switch.

### 3.4.3 Target moments of interest

One targeted moment of interest when calibrating the initial steady state of the model is the 3% job separation rate of occupations that were initially nonspecific ( $JZ1977 = \text{low}$ ) at the beginning of the CPS sample period (starting point of the blue line in Figure 3). Other targeted moments used to calibrate the model’s initial steady state include the zero wage penalties after an unemployment spell faced by both non-occupation and occupation switchers, whose previous occupation has remained nonspecific throughout the SIPP sample period ( $JZ1977 = \text{low}$ ,  $JZ_{\text{new}} = \text{low}$ ). They are interpreted as labor market characteristics of nonspecific occupations ( $JZ1977 = \text{low}$ ) at the beginning of the CPS sample period, where previous workers, both occupation switchers and non-occupation switchers, experience no loss in occupation-specific capital hence zero wage loss. This is consistent with the interpretation of the targeted 3% job separation rate of occupations that were nonspecific ( $JZ1977 = \text{low}$ ) at the beginning of the CPS sample period as the hypothetical job separation rate had these occupations remained nonspecific over time.

The average length of occupation-specific training  $1/\mu$  and the output gap  $\tau$  are the occupation specificity parameters of the model. First,  $1/\mu$  is exogenously set according to the definition of job zones in the DOT/O\*NET. In the initial steady state,  $1/\mu = 8$ , where nonspecific occupations are defined to have on average 8 weeks of occupation-specific training. Then,  $\tau$  in the initial steady state is set so that together with  $1/\mu = 8$ , and with the remaining parameter values, it produces the targeted 3% job separation rate and the zero wage penalties experienced by non-occupation and occupation switchers whose previous occupation was initially nonspecific and has remained nonspecific over time.

Table 5: Model and target data moments

	Model moment	Target moment	Source
Job separation rate, monthly	0.030	0.030	CPS
Job finding rate, monthly	0.227	0.200	
Share of unemployment spells with occupation switch	0.552	0.600	
Wage penalty, occupation switchers	0.007	0.000	SIPP, Table 14
Wage penalty, non-occupation switchers	0.004	0.000	(in the appendix)
Value of unemployment	0.774	0.710	Hall and Milgrom (2008)
Market tightness	0.500	0.500	

Table 5 shows that with the parameter values in Table 4, the model moments match the targeted data moments that characterize  $JZ1977 = \text{low}$  occupations at the beginning of the CPS sample period.

In short, the model is calibrated to match the 3% job separation rate and other data moments characterizing nonspecific ( $JZ1977 = 1$ ) occupations at the beginning of the CPS sample period. Next, I discuss the experiments conducted with the model.

Table 6: Change in occupation specificity parameters  $\tau$  and  $1/\mu$  after occupations become more specific, by initial specificity

Case	Parameters	Source
JZ1977 = low, JZnew = low	$1/\mu = 8,$ $\tau = 0.000$	Target moments in Table 5 (initial steady state)
① JZ1977 = low, JZnew = medium	$1/\mu = 48,$ $\tau = 0.455$	DOT/O*NET, Additional wage loss for occupation switchers = $-0.054$
② JZ1977 = medium, JZnew = medium	$1/\mu = 48,$ $\tau = 0.742$	DOT/O*NET, Additional wage loss for occupation switchers = $-0.143$
③ JZ1977 = medium, JZnew = high	$1/\mu = 96,$ $\tau = 0.943$	DOT/O*NET, Additional wage loss for occupation switchers = $-0.135$
④ JZ1977 = high, JZnew = high	$1/\mu = 96,$ $\tau = 0.996$	DOT/O*NET, Additional wage loss for occupation switchers = $-0.176$

Note: By the definition of job zones (JZ) in the DOT/O\*NET of any time period, occupations are rated on a five-point scale with higher values representing higher occupation specificity (longer occupation-specific training). The five job zones are aggregated to three levels of occupation specificity (low (JZ = 1), medium (JZ = 2 or 3), and high (JZ = 4 or 5)) to reduce the number of groups. Occupations in low, medium, high job zones require an average length of 8, 12, and 24 weeks of occupation-specific training respectively.

The initial steady-state values are determined to match the target moments listed in Table 5. In each of the next four experiments of making occupations more specific, the average length of occupation-specific training  $1/\mu$  before (after) the increase in occupation specificity is first set according to the definition of job zones in the DOT/O\*NET. The output gap  $\tau$  between trained and nontrained workers is then set so that together with the given  $1/\mu$ , the model counterpart of the additional wage penalty faced by occupation switchers (relative to non-occupation switchers) matches the additional wage penalty faced by occupation switchers of the same case as observed in the SIPP (see the appendix).

### 3.5 Experiments

After calibrating the initial steady state of the model, four experiments are conducted with the model to predict the decline in the job separation rates by initial specificity (JZ1977 = low, medium, high). Each experiment is conducted by simulating the same model after increasing the values of the two occupation specificity parameters, the average length of occupation-specific training  $1/\mu$  and output gap  $\tau$ , holding the remaining parameters at their initially steady-state values. First,  $1/\mu$  is increased according to the definition of job zones in the DOT/O\*NET. Then,  $\tau$  is increased so that jointly with the increased  $1/\mu$ , the model replicates the increase in the estimated wage penalty faced by occupation switchers (relative to non-occupation switchers) when their previously held occupation has become more specific (more on the estimated wage penalty from the SIPP is provided the appendix). These predicted declines in the job separation rates by initial specificity will be compared with the data. They are then aggregated to also compare the model's prediction of the decline in the aggregate job separation rate with the data. The model will also be evaluated by whether it finds that the group of occupations that were initially nonspecific and have become more specific indeed contributes the most to the decline in the aggregate job separation rate, as found in the empirical analysis.

The first experiment makes all the initially nonspecific occupations at the beginning of the CPS sample period more specific (JZ1977 = low, JZnew = medium). The model's predicted job separation rate after this increase in specificity (marked as circled point one in Figure 9 in Section 3.7.1) is compared with the actual job separation rate of initially nonspecific (JZ1977 = low) occupations at the end of the CPS sample period. First,  $1/\mu$  is increased from 8 to 24 (weeks). Then,  $\tau$  is increased from the initial steady-state value  $\tau = 0$  to 0.455 so that together with  $1/\mu = 24$ , the model generates the 5.4 p.p. additional wage penalty faced by occupation switchers, relative to non-occupation switchers, whose previous occupation has become more specific after being initially nonspecific (JZ1977 = low, JZnew = medium).

The second experiment predicts and compares the job separation rate of initially medium-specific (JZ1977 = medium) occupations at the beginning of the CPS sample period (marked as circled point two in Figure 9 in Section 3.7.1) with the data. First,  $1/\mu$  is set to 24 (weeks). Then,  $\tau$  is set to  $\tau = 0.742$  so that together with  $1/\mu = 24$ , the model produces the 14.3 p.p. additional wage penalty faced by occupation switchers, relative to non-occupation switchers, whose previous occupation was initially medium-specific and has remained medium-specific (JZ1977 = medium, JZnew = medium).

The third experiment makes all the initially medium-specific occupations more specific (JZ1977 = medium, JZnew = high) and predicts their job separation rate (marked as circled point three in Figure 9 in Section 3.7.1). This will be compared to the actual job separation rate of initially medium-specific (JZ1977 = medium) occupations at the end of the CPS sample period. First,  $1/\mu$  is increased from 24 to 48 (weeks). Then,  $\tau$  is increased from  $\tau = 0.742$  to  $\tau = 0.943$  so that together with  $1/\mu = 48$ , the model matches the 13.5 p.p. additional wage penalty faced by occupation switchers, relative to non-occupation switchers, whose previous occupation was initially medium-specific and has become more specific (JZ1977 = medium, JZnew = high).

The fourth experiment predicts and compares the job separation rate of initially high-specific (JZ1977 = high) occupations at the beginning of the CPS sample period with the data. Because these occupations are already at their highest level of occupation specificity, this predicted job separation rate is set to be the predicted job separation rate at the end of the CPS sample period as well. Both are marked as circled point four in Figure 9 in Section 3.7.1. First,  $1/\mu$  is set to 48 (weeks). Then,  $\tau$  is set to  $\tau = 0.996$  so that together with  $1/\mu = 48$ , the model produces the 17.6 p.p. additional wage penalty faced by occupation switchers, relative to non-occupation switchers, whose previous occupation was initially high-specific and has remained high-specific (JZ1977 = high, JZnew = high).

Finally, based on the predicted decline in the job separation rates by initial specificity (JZ1977), the model predicts the decline in the aggregate job separation rate. This is done by aggregating the predicted decline in the job separation rates by JZ1977 = low, medium, high occupations using employment shares by JZ1977 at the beginning of the sample period from the CPS.<sup>15</sup> The model

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<sup>15</sup>The model has no say about changes in employment shares across different job zones because job zones are assumed to be isolated labor markets. This model setup is motivated by the shift-share decomposition result that shift in employment shares across job zones does not contribute much to the decline in the aggregate job separation rate. Therefore, shares are fixed, using 1983 shares brought externally from the CPS.

will also show (and compare to the data) how much of the decline in the aggregate job separation can be accounted for by the group of occupations that were initially nonspecific and have become more specific over time.

The values for  $1/\mu$  and  $\tau$  under the initial steady state and the four experiments discussed above are presented in Table 6.

### 3.6 Mechanism – why the job separation rate falls after occupations become more specific

This section discusses how increasing occupation specificity reduces job separations before presenting the model's predictions.

The decline in the job separation rate from increasing occupation specificity is primarily driven by the decline in job separations by trained workers who have accumulated occupation-specific human capital. This is shown in Figure 7, which plots for nontrained and trained workers separately, the change in their reservation productivity  $z^{sep}$  as the average length of occupation-specific training  $1/\mu$  (left) and the output gap  $\tau$  between trained and nontrained workers (right) increases. If an employed worker's idiosyncratic productivity falls below  $z^{sep}$ , the worker and employer choose to separate. A falling  $z^{sep}$  means falling job separation rates because it becomes less likely that workers fall below the cutoff  $z^{sep}$ . When occupation specificity increases, either by the increase in  $1/\mu$  or the increase in  $\tau$ , trained workers' reservation productivities decline and hence they choose to separate less. Nontrained workers' reservation productivities do not change much.

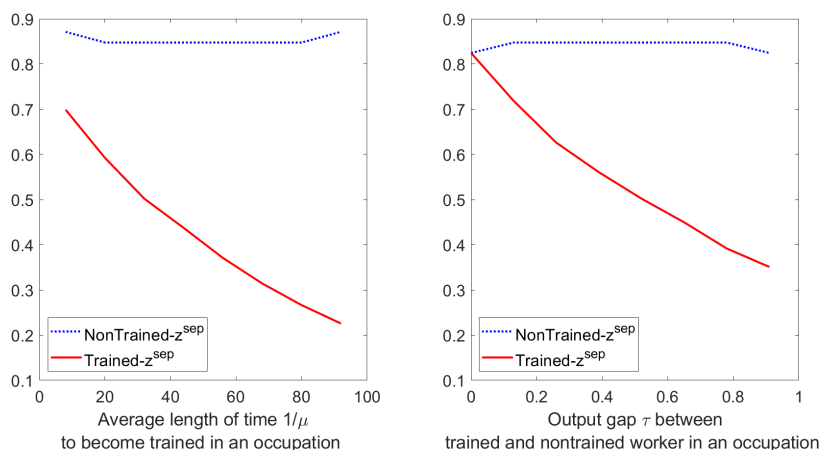


Figure 7: Reservation productivities of nontrained and trained workers

Note: Figure 7 plots the change in the reservation productivity  $z^{sep}$  as the average length of occupation-specific training (left) and the output gap between trained and nontrained workers (right) increases. If an employed worker's idiosyncratic productivity falls below  $z^{sep}$ , the worker and employer choose to separate. Falling  $z^{sep}$  means it becomes less likely that workers fall below the cutoff  $z^{sep}$  and separate from their job. The left panel plots  $z^{sep}$  of nontrained and trained workers as the average length of occupation-specific training time  $1/\mu$  increases, holding the output gap fixed at  $\tau = 0.742$ . The right panel plots  $z^{sep}$  of nontrained and trained workers as the output gap between trained and nontrained workers increases, holding the average length of occupation-specific training time fixed at  $1/\mu = 12$ .

When occupations become more specific in the model, the output gap between nontrained and

trained workers or the length of occupation-specific training time increases. Trained workers are less motivated to separate by either definition of increasing occupation specificity. A larger output gap means that the trained worker's occupation-specific human capital becomes less transferable to a different occupation. If trained workers become unemployed and are then hit by the exogenous occupation-switching shock, they become nontrained workers, lacking a larger amount of occupation-specific human capital they must acquire to become trained in the new occupation, which translates into lower wages. Hence trained workers choose to separate less. The intuition is similar for the case of longer occupation-specific training. If trained workers become unemployed and are then hit by the occupation-switching shock, they must undergo a longer period as a nontrained worker earning lower wages. Therefore trained workers are motivated to not separate from their job. Meanwhile, nontrained workers' incentives to separate are not affected much by increasing occupation specificity.

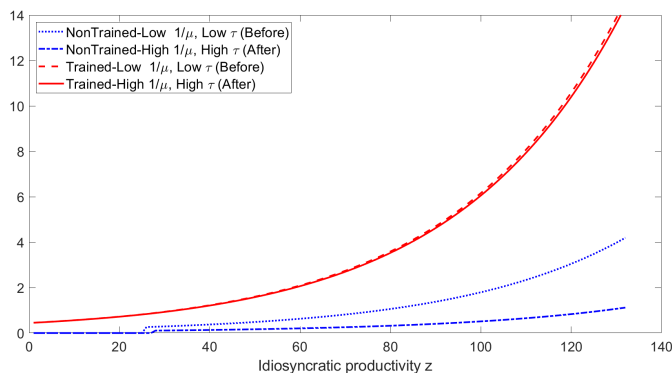


Figure 8: Wage functions of nontrained and trained workers

Note: Figure 8 plots the wage functions of nontrained and trained workers before the increase in occupation specificity (low  $1/\mu = 48$ , low  $\tau = 0.742$ ) and after the increase in occupation specificity (high  $1/\mu = 96$ , high  $\tau = 0.943$ ). From Table 6, the increase in occupation specificity of initially medium-specific occupations means that  $(\tau, 1/\mu)$  is initially  $(\tau = 0.742, 1/\mu = 48)$  and increases to  $(\tau = 0.943, 1/\mu = 96)$ . Hence the red dashed line and blue dotted line would be the wage functions (for trained and nontrained workers respectively) when occupations are initially medium-specific, and the solid red line and long dashed blue line would be the wage functions (for trained and nontrained workers respectively) when occupations have become more specific (to high-specific) after being initially medium-specific. The vertical lines are at the reservation productivities.

The model implies that following the increase in occupation specificity, trained workers are willing to accept lower wages at the same level of productivity to avoid job separations. This is shown in Figure 8, which plots the wage functions for nontrained and trained workers before and after occupations become more specific. The wage function for the nontrained workers shifts down, in particular, because they are less productive due to the lack of a larger amount of occupation-specific capital by higher  $\tau$ . When occupations become more specific, trained workers anticipate the possibility of earning such lower wages (higher  $\tau$ ) for a longer time (longer  $1/\mu$ ) as a nontrained worker at a different occupation following the separation from their current job. Hence they accept lower wages at their current job. At the same level of productivity, wage functions for the trained workers shift down after the increase in occupation specificity. There are also low productivity trained worker-firm matches that would not have existed before the increase in occupation specificity. This

Table 7: Job separation rates before and after occupations become more specific, by initial specificity

Before → After	Job sep. rate (monthly)	Job finding rate (monthly)
JZ1977 = low → JZnew = medium	0.030 (targeted) → 0.006	0.227 (targeted) → 0.252
JZ1977 = medium → JZnew = high	0.006 → 0.010	0.266 → 0.194
JZ1977 = high → JZnew = high	0.010 → 0.010	0.189 → 0.189

Note: Table 7 lists the job separation rates (monthly) and job finding rates (monthly) predicted by the calibrated model before and after occupations become more specific by initial specificity.

is observed in the leftward shift in the vertical lines in the wage functions, which means the decrease in the reservation productivity of the trained workers.

### 3.7 Results

#### 3.7.1 Labor market outcomes after occupations become more specific, by initial specificity, predicted by the model

Table 7 lists the model’s predictions on the job separation rates and job finding rates after occupations become more specific by initial specificity. Figures 9 and 10 are the visualization of the model’s predictions compared with the data. The circled numbers indicate the order in which the experiments were conducted. Each experiment was conducted by simulating the same model after increasing the occupation specificity parameters accordingly, holding the remaining parameters at their initial steady-state values.

The model predicts a twice-fold larger decline in its job separation rate (3% to 0.6% predicted by the model; solid blue line in Figure 9) compared to the data (3% to 1.5% in the data; dashed blue line in Figure 9) after occupations become more specific. The model is also able to match the empirical finding (Figure 3 in Section 2.2, which is reproduced as dashed lines in Figure 9 below) that the average job separate rate is highest for the initially nonspecific (JZ1977 = low) occupations; the solid blue line (JZ1977 = low) is above the solid red or green (JZ1977 = medium, high) lines in Figure 9. The model also replicates that the observed change in the job separation rate in response to the increase in specificity within occupations is the largest for the initially nonspecific (JZ1977 = low) occupations.

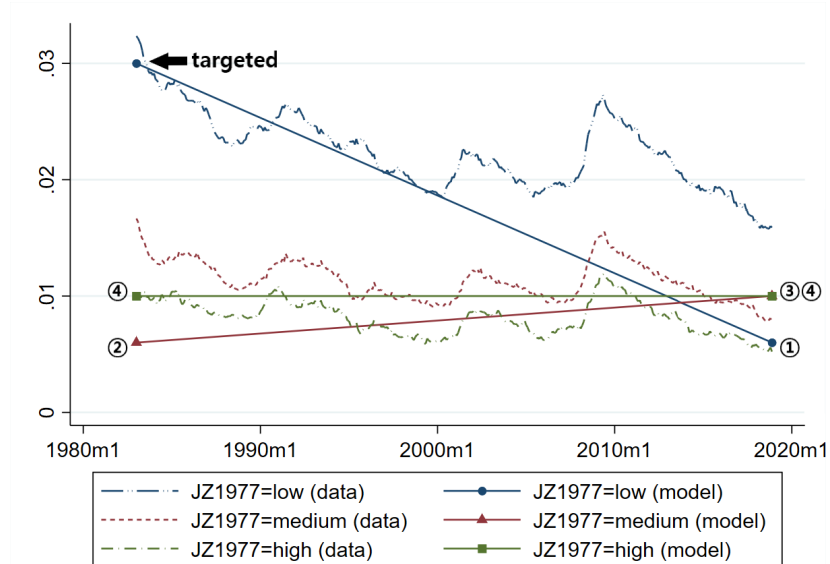


Figure 9: Job separation rates over time by initial specificity: model (solid) vs. data (dashed)  
 Note: Figure 9 plots the model's predicted (solid lines) job separation rates after occupations become more specific by initial specificity, compared to the data (dashed lines). The job separation rate of initially nonspecific (JZ1977 = low) occupations at the beginning of the sample period (labeled with arrow) is targeted to calibrate the initial steady state of the model. The remaining five points marked with circled numbers (job separation rates of the JZ1977 = low occupations at the end of the sample period, the job separation rates of the JZ1977 = medium occupations at the beginning and end of the sample period, and the job separation rates of the JZ1977 = high occupations at the beginning and end of the sample period) are predicted by the model, each resulting from four separate experiments. The circled numbers indicate the order in which the experiments were conducted. Each experiment simulates the same model after increasing the occupation specificity parameters accordingly, holding the remaining parameters at their initial steady-state values.

The model also captures the empirical fact that job finding rates do not change much in response to the increase in occupation specificity (Figure 10). Several forces result in the job finding rates not moving much as occupations become more specific. Because trained workers become less motivated to separate after they are hired, firms find trained workers more desirable and post more vacancies for trained workers, which increases the job finding rate of trained workers. However, because trained workers separate less as occupation specificity increases, the share of trained workers among the unemployed falls, resulting in the overall job finding rate not being affected by the trained workers. The nontrained workers seem less desirable because they are less productive (larger  $\tau$ ) for a longer time (larger  $1/\mu$ ). This is offset by the fact that they will become trained workers after  $1/\mu$  weeks on average, who, in turn, are desirable because they separate less following the increase in occupation specificity. If  $1/\mu$  or  $\tau$  becomes too large, however, nontrained workers will become less desirable, reducing their job finding rate, which will then decrease the overall job finding rate. The decreasing effect would also be amplified because the share of nontrained workers among the unemployed rises as occupations become more specific.



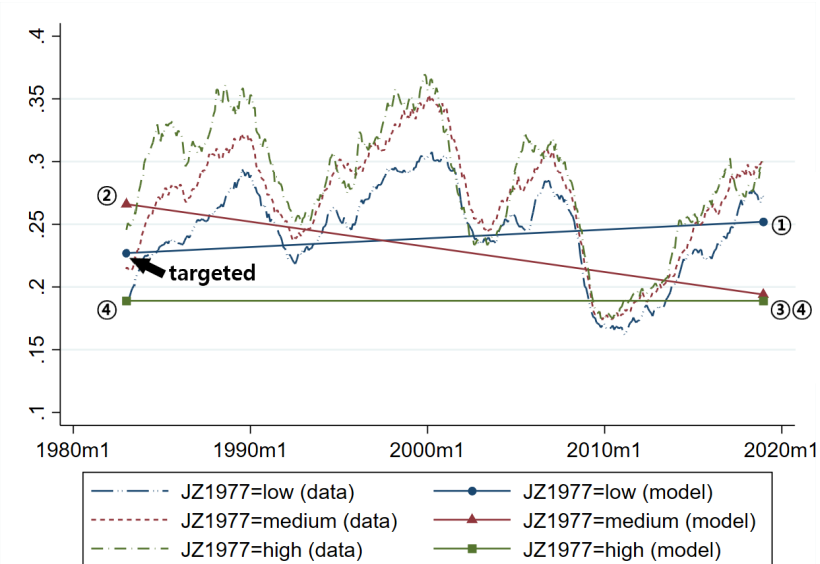


Figure 10: Job finding rates over time by initial specificity: model (solid) vs. data (dashed)

Note: Figure 10 plots the model's predicted (solid lines) job finding rates after occupations become more specific by initial specificity, compared to the data (dashed lines). The job finding rate of initially nonspecific ( $JZ1977 = \text{low}$ ) occupations at the beginning of the sample period (labeled with arrow) is targeted to calibrate the initial steady state of the model. The remaining five points marked with circled numbers (job finding rate of the  $JZ1977 = \text{low}$  occupations at the end of the sample period, the job finding rates of the  $JZ1977 = \text{medium}$  occupations at the beginning and end of the sample period, and the job finding rates of the  $JZ1977 = \text{high}$  occupations at the beginning and end of the sample period) are predicted by the model, each resulting from four separate experiments. The circled numbers indicate the order in which the experiments were conducted. Each experiment simulates the same model after increasing the occupation specificity parameters accordingly, holding the remaining parameters at their initial steady-state values.

### 3.7.2 Decline in the aggregate job separation rate predicted by the model

In Figure 11, the solid lines plot the normalized aggregate job separation rate and the counterfactual predicted by the model. The model's predicted aggregate job separation rate at the start (end) of the sample period is the weighted sum (weights are employment shares at the start of the sample period from the CPS) of (i) the targeted 3% job separation rate of  $JZ1977 = \text{low}$  occupations at the start of the sample period (the model's predicted job separation rate of  $JZ1977 = \text{low}$  occupations at the end of the sample period), (ii) the model's predicted job separation rate of  $JZ1977 = \text{medium}$  occupations at the start of the sample period (end of the sample period), and (iii) the model's predicted job separation rate of  $JZ1977 = \text{high}$  occupations at the start of the sample period (end of the sample period). The model's counterfactual aggregate job separation rate is obtained by replacing the model's predicted job separation rate of  $JZ1977 = \text{low}$  occupations at the end of the sample period with the targeted 3% job separation rate of  $JZ1977 = \text{low}$  occupations at the start of the sample period. To compare the extent of the change in the aggregate job separation rate

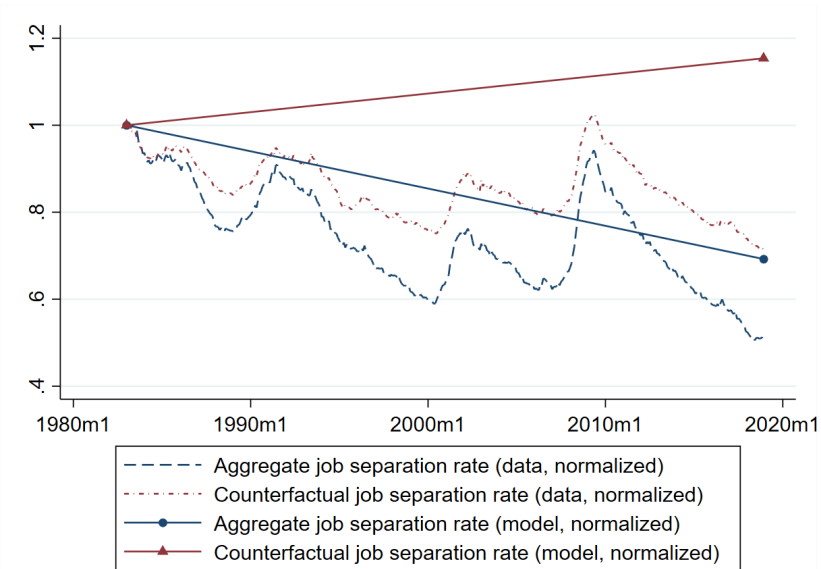


Figure 11: Aggregate job separation rate and counterfactual: model (left) vs. data (right)

Note: The solid lines plot the aggregate job separation rate and the counterfactual aggregate job separation rate predicted by the model using the model's predicted decline in the job separation rates by initial specificity over time (listed in the first column of Table 7). The model's predicted aggregate job separation rate at the start (end) of the sample period is the weighted sum (weights are employment shares at the start of the sample period from the CPS) of (i) the targeted 3% job separation rate of JZ1977 = low occupations at the start of the sample period (the model's predicted job separation rate of JZ1977 = low occupations at the end of the sample period), (ii) the model's predicted job separation rate of JZ1977 = medium occupations at the start of the sample period (end of the sample period), and (iii) the model's predicted job separation rate of JZ1977 = high occupations at the start of the sample period (end of the sample period). The model's counterfactual job separation rate is obtained by replacing the model's predicted job separation rate of JZ1977 = low occupations at the end of the sample period with the targeted 3% job separation rate of JZ1977 = low occupations at the start of the sample period. The dashed lines are the data counterpart of the aggregate job separation rate and the counterfactual job separation rate. The series are normalized by their initial levels.

predicted by the model with the data, I normalize the series by their initial levels, respectively, as in Figure 11. In the data, the aggregate job separation rate declines by 50%, from 2.2% to 1.1% (the dashed blue line plots the aggregate job separation rate in the data normalized by its initial level). The model predicts that the aggregate job separation rate declines by 30%, from 1.3% to 0.9% (the solid blue line plots the model's predicted aggregate job separation rate normalized by its initial level). Hence the model captures 60% of the decline in the aggregate job separation rate. The model can also capture the empirical fact that the falling job separation rate of workers in occupations that were initially nonspecific and have become more specific plays the most important role in the falling aggregate job separation rate. In the data, the group of occupations that were initially nonspecific and have become more specific over time contributes to about half the decline in the aggregate job separation rate (dashed red line). In the model, without the decline in the job separation rate of this group, the aggregate job separation rate would be increasing over time (solid red line).

## 4 Conclusion

The previous literature has noted that the aggregate job separation rate has been declining in the United States. This paper documents that (i) required occupation-specific training has increased within occupations and that (ii) the share of employment in occupations that require more occupation-specific training has increased over time. A shift-share decomposition shows that within-occupation increase in occupation-specific training accounts for most of the decline in the aggregate job separation rate. I build a search-and-matching model where the increase in occupation-specific training within occupations reduces job separations. The model captures 60% of the decline in the aggregate job separation rate observed in the data. In the model, when occupations become more specific (require more occupation-specific training), workers accept lower wages at the same level of productivity to avoid job separations, in turn, to avoid switching to a different occupation where previous occupation-specific human capital is less applicable. My analysis suggests the need for policies such as worker retraining to make human capital more portable across occupations.

In the current model, job separation decisions are endogenous, but occupation switching is assumed to be an exogenous shock. In the companion paper, I endogenize occupation switching and job separations. When unemployed workers are allowed to choose whether or not to switch occupations, the trained workers, in particular, become more attached to their previous occupation after occupations become more specific. This results in longer unemployment spells than when occupations switching is assumed to be exogenous.

Moreover, the current model takes the increase in occupation-specific training as exogenously given. Future research should investigate why occupations have become more specific over the past four decades and endogenize the increase in occupation specificity in the model. This is relevant for designing policies to facilitate the reallocation of workers between occupations.

## A Job Zones

### A.1 Job zones as a proxy for occupation specificity

According to O\*NET documentation (Oswald et al. 1999), job zones are “intended to be a measure of the required level of specific occupational training and experience.” Hence I use the job zones of an occupation as a proxy for the specificity of an occupation. An occupation becoming more specific means that human capital acquired and used in this occupation becomes more specific to this occupation and less transferable to a different occupation.

Besides the definition of job zones mentioning “occupation specificity,” other pieces of evidence that job zones proxy for “occupation specificity” include that the wage decline accompanied by switching occupations, as opposed to switching employers, after unemployment is larger, the higher the previous occupation’s job zone (results provided below). Also, the probability of occupation switching after unemployment is lower the higher the previous occupation’s job zone (figure provided below). These are consistent with the intuition that the human capital associated with occupations requiring more occupation-specific training is more occupation-specific, hence making occupation-switching more costly. More discussion on how job zones are defined, how they differ from general education and routine task intensity, and why job zones are a proxy for occupation specificity is provided below.

#### a. Specific vocational job preparation in the DOT (1977, 1991)

The DOT (1977, 1991) contains a measure called specific vocational job preparation (SVP) for each occupation. According to the DOT, it is “the amount of lapsed time required by a typical worker to learn the techniques, acquire the information, and develop the facility needed for average performance in a specific job-worker situation... Specific vocational training includes training given in any of the following circumstances: vocational education, apprenticeship training, in-plant training, on-the-job training and essential experience in other jobs.”

Specific vocational training includes training given in any of the following circumstances:

- Vocational education (high school; commercial or shop training; technical school; art school; and that part of college training which is organized around a specific vocational objective)
- Apprenticeship training (for apprenticeable jobs only)
- In-plant training (organized classroom study provided by an employer)
- On-the-job training (serving as learner or trainee on the job under the instruction of a qualified worker)
- Essential experience in other jobs (serving in less responsible jobs which lead to the higher grade job or serving in other jobs which qualify).

Each occupation is rated on a nine-point scale, with higher values representing longer training. The following Table 8 is the explanation of SVP as written in the DOT.

Table 8: Specific Vocational Preparation (SVP)

SVP Level	Time
1	Short demonstration only
2	Anything beyond short demonstration up to and including 1 month
3	Over 1 month up to and including 3 months
4	Over 3 months up to and including 6 months
5	Over 6 months up to and including 1 year
6	Over 1 year up to and including 2 years
7	Over 2 years up to and including 4 years
8	Over 4 years up to and including 10 years
9	Over 10 years

Source: DOT (1977, 1991).

#### b. Job zones in O\*NET (since 2000)

A job zone is a group of occupations that are similar in how much education, related experience, and on-the-job training people need to do the work. Each occupation is rated on a five-point scale with higher values representing more required preparation. It is stated in O\*NET that job zones correspond to the SVP in the DOT (1977, 1991).

The five job zones are (as explained in O\*NET):

Job Zone 1 – occupations that need little or no preparation (corresponds to SVP below 4)

Job Zone 2 – occupations that need some preparation (corresponds to SVP 4 to below 6)

Job Zone 3 – occupations that need medium preparation (corresponds to SVP 6 to below 7)

Job Zone 4 – occupations that need considerable preparation (corresponds to SVP 7 to below 8)

Job Zone 5 – occupations that need extensive preparation (corresponds to SVP 8 and above)

#### c. Correlation with general education and routine task intensity

This section discusses how the job zone measure by occupation is related to general education and the routine task intensity index.

## **General education (high school dropout/high school grad/some college/college grad/post college)**

High school or college education could be understood as education of a general nature that does not have a recognized, fairly specific occupational objective. In contrast, SVP or job zones emphasize training with an occupation-specific objective. One criterion for job zones is whether a high school or college degree is required. However, O\*NET states that job zones succeed the SVP measure, which is defined to be the degree of required specific vocational job preparation to be an average performer in that occupation, and that they are “intended to be a measure of the required level of specific occupational training and experience” (Oswald et al. 1999).

Nevertheless, there is a positive correlation between general education and required occupation-specific training: college graduates tend to work in occupations rated higher in terms of SVP or job zone. Below, using CPS data in 2000 (midpoint of the CPS sample period 1983–2018), Figure 12 plots the share of employment by job zone for noncollege and college graduates. In the right panel of Figure 12, there is less variation of job zones within college graduates, with the share of employment more skewed towards occupations in job zones 4 and 5.

At the same time, there is sufficient variation of job zones within noncollege workers, who are the majority of workers in the United States. In the left panel of Figure 12, within workers without a college degree, the share of employment is fairly uniform across all job zones.

As discussed in the paper, the largest contributor to the decline in the aggregate job separation rate are the occupations that were not specific four decades ago ( $JZ_{1977} = 1$ ) and have become more specific over time. These occupations are mostly held by noncollege graduates. The increase in required occupation-specific training that is driving the aggregate job separation rate decline is experienced within noncollege graduates. The aggregate job separation rate is not falling because more workers are becoming college graduates.

## **Routine Task Intensity**

The routine task intensity (RTI) index is a summary measure of the routineness of an occupation (whether the tasks carried out in this occupation are easily be automated by computers). Following Autor and Dorn (2013), I use the 1977 DOT to compute the RTI index for each occupation. The RTI index for each occupation is defined to be the difference between the log of required routine task input and the sum of the log of required abstract input and the log of required manual task input for each occupation.

Table 9 shows the average, minimum and maximum value of the RTI by SVP from the 1977 DOT. There is a negative correlation (correlation coefficient  $-0.17$ ) between an occupation’s required level of occupation-specific training and RTI: occupations with lower required occupation-specific training tend to be routine intensive (higher RTI index). However, the relation is not monotonic; occupations with mid-range  $SVP = 4, 5, 6$  (or in job zone 2 or 3) are the most routine-intensive.

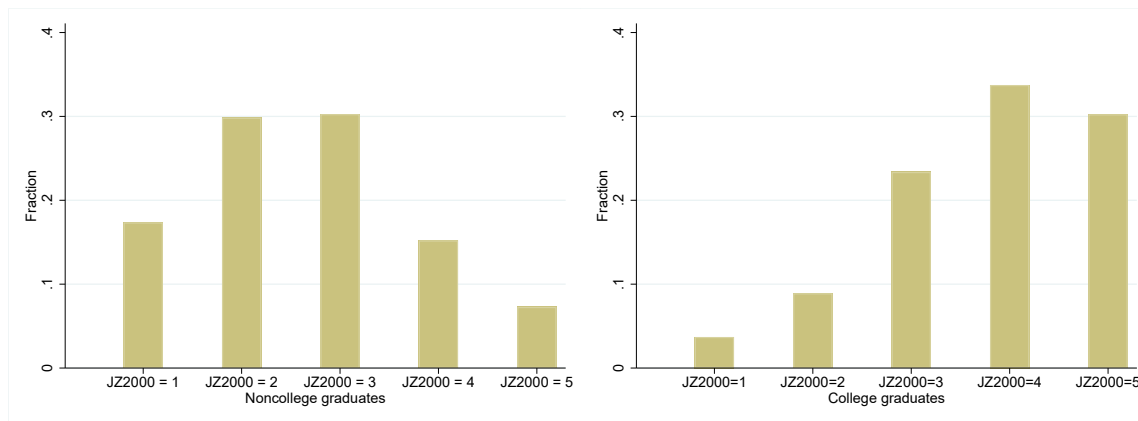


Figure 12: Employment share by occupation specificity, noncollege (left) and college graduates (right)

Source: Monthly CPS (2000), DOT/O\*NET.

Note: The left panel of Figure 12 plots the share of employment by occupation specificity (in the year 2000, measured by job zone 2000), limiting the sample to noncollege graduates. The right panel of Figure 12 plots the share of employment by occupation specificity (measured by job zone 2000), limiting the sample to college graduates. By the definition of job zones (JZ) in the DOT/O\*NET of any time period, occupations are rated on a five-point scale with higher values representing higher occupation specificity (longer occupation-specific training).

### Evidence that job zones proxy for occupation specificity, unlike general education and routine task intensity

Job zones exhibit labor market outcomes consistent with the intuition that they proxy for “occupation specificity,” unlike general education or routine task intensity. The intuition is that the human capital accumulated while working in occupations requiring more occupation-specific training is more specific to the occupation, thereby making occupation-switching more costly.

Unemployed workers who used to work in occupations requiring more occupation-specific training have a lower probability of switching occupation out of unemployment (from the CPS 1983–2018). Meanwhile, a higher probability of occupation switching out of unemployment is observed for workers with higher general education and workers who previously worked in routine occupations (see Figures 13–15).

Unemployed workers who used to work in occupations requiring more occupation-specific training face larger wage cuts upon reemployment at a different occupation (from the SIPP 1985–2013). This still holds conditioning on education and routine task intensity (see results in Section D). Different results are observed for general education and routine task intensity. There is no difference in the wage penalty associated with occupation switching for workers of different levels of general education. Meanwhile, the wage penalty for switching occupations out of unemployment is smaller for workers previously employed in occupations of higher routine task intensity (see Table 10).

Table 9: Summary statistics for RTI by SVP (1977 DOT)

SVP	mean	min	max
2	1.077	-0.861	2.201
3	1.258	-1.222	4.933
4	2.039	-1.734	5.811
5	1.427	-1.693	6.417
6	1.579	-2.108	6.216
7	0.617	-2.41	5.114
8	0.928	-1.309	4.284

Source: DOT(1977), Autor and Dorn (2013).

Note: By the definition of specific vocational job preparation (SVP) for each occupation in the 1977 DOT, occupations are rated on a nine-point scale with higher values representing higher occupation specificity, with SVP = 1 the lowest and SVP = 9 the highest. The set of 338 occupations has no occupations with SVP = 1 or SVP = 9; hence they are omitted in Table 9, which lists the summary statistics (mean, minimum, maximum) of the distribution of the routine task intensity (RTI) index for each SVP group of occupations.

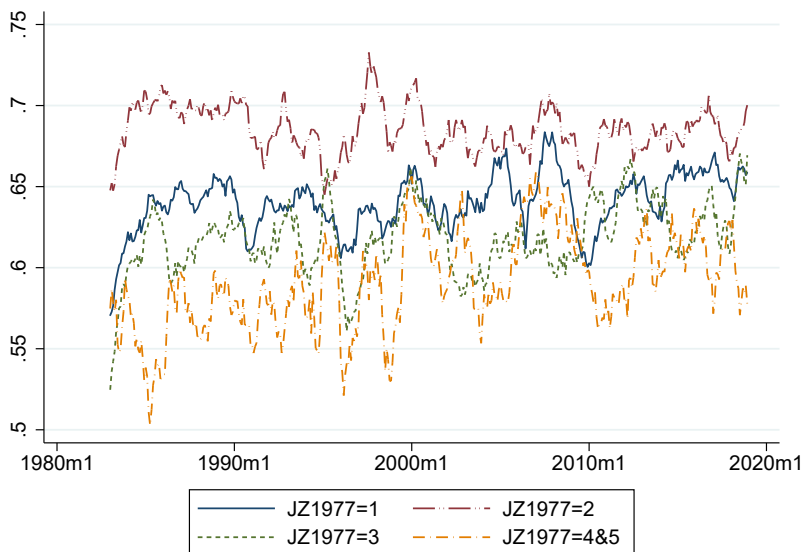


Figure 13: Share of unemployment spells that end with an occupation switch, by job zone

Source: Monthly CPS (1983–2018).

Note: The figure plots the share of unemployment spells that end with an occupation switch by initial occupation specificity (fixed at 1977 job zone) of the occupation held before the unemployment spell. By the definition of job zones (JZ) in the DOT/O\*NET of any time period, occupations are rated on a five-point scale with higher values representing higher occupation specificity (longer occupation-specific training).



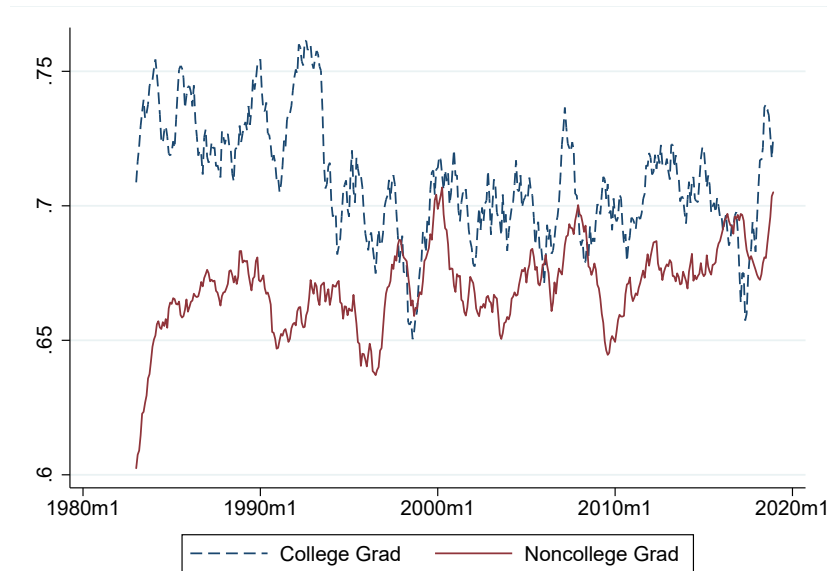


Figure 14: Share of unemployment spells that end with an occupation switch, by education  
 Source: Monthly CPS (1983–2018).  
 Note: The figure plots the share of unemployment spells that end with an occupation switch by the level of general education of the worker (college graduate or noncollege graduate).

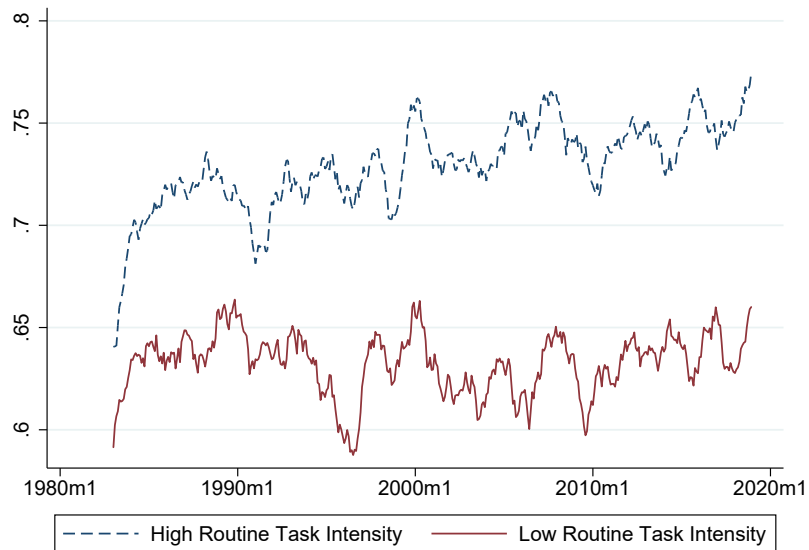


Figure 15: Share of unemployment spells that end with an occupation switch, by routine task intensity  
 Source: Monthly CPS (1983–2018).  
 Note: The figure plots the share of unemployment spells that end with an occupation switch by the routine task intensity (“high” if above the median routine task intensity) of the occupation held before the unemployment spell.

Table 10: Wage penalty from occupation switching, by general education and routine task intensity

	(1)	(2)	(3)
	$\Delta \log wage$	$\Delta \log wage$	$\Delta \log wage$
$\mathbb{I}\{occ.switch\}$	-0.091*** (0.028)	-0.084*** (0.014)	-0.110*** (0.028)
$education \times \mathbb{I}\{occ.switch\}$	0.011 (0.012)		0.011 (0.012)
$education$	-0.020** (0.010)		-0.020** (0.010)
$RTI \times \mathbb{I}\{occ.switch\}$		0.015*** (0.006)	0.015** (0.006)
$RTI$		-0.006 (0.004)	-0.006 (0.004)
$Constant$	0.020 (0.021)	-0.023** (0.010)	0.025 (0.021)
$N$	12495	12495	12495

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Source: SIPP (1985–2013).

Note: The table reports results from the regression of  $\Delta \log wage$ , the change in log wage after the unemployment spell, on the interactions of the indicator  $\mathbb{I}\{occ.switch\}$  of whether the spell ends in an occupation switch, years of education, and routine task intensity (RTI). Standard errors are in parentheses. Longitudinal panel weights are used in all regressions.

## A.2 Summary

Unlike general education or routine task intensity, job zones emphasize training with an occupation-specific objective. Job zones exhibit labor market outcomes consistent with the intuition that they proxy for “occupation specificity.” Nevertheless, there is a correlation between job zones and general education or routine task intensity. In all the regressions in the paper (one on the effect of increasing occupation specificity on the job separation rate and the other on the effect of increasing occupation specificity on the wage penalty faced by occupation switchers), I add general education attainment and routine task intensity, in addition to age, sex, race, as controls. Adding these controls does not affect the regression estimates.

## B Evidence that human capital is occupation-specific and that job zones proxy for occupation specificity

This section provides evidence that job zones (JZ) are a proxy for the specificity of an occupation. An occupation being more specific means that human capital accumulated in this occupation is less transferable to a different occupation. By the definition of job zones (JZ) in the DOT/O\*NET of any time period, occupations are rated on a five-point scale with higher values representing higher occupation specificity (longer occupation-specific training).<sup>16</sup> Evidence that job zones proxy for occupation specificity is the result that the wage cuts after an unemployment spell are larger the more specific (higher job zone) the occupation before the unemployment spell. These wage cuts, which increase in the specificity of the previously held occupation, are observed only among workers who switched occupations after the unemployment spell, not those who switched employers after the unemployment spell.

This conclusion is reached by starting from the simplest Regression (1) where the change in log wage after the unemployment spell is regressed on a constant, and expanding the regression to Regression (5) in multiple steps.

In Regression (1),  $\Delta \log wage$ , the change in log wage after the unemployment spell, is regressed on a constant. There is an average wage penalty of 7.3% after an unemployment spell.

In Regression (2),  $\Delta \log wage$  is regressed on the indicator  $\mathbb{I}\{occ.switch\}$ , which takes a value = 1 when the spell ends in an occupation switch (occupation after the unemployment spell is different from the occupation before the unemployment spell). Most of the 7.3% wage penalty after an unemployment spell comes from occupation switches.

In Regression (3),  $\Delta \log wage$  is regressed on the set of indicators  $\mathbb{I}\{JZ1977 = j\}$  marking the specificity of the previously held occupation, measured by  $JZ1977 = j$  for  $j = 2, 3, 4, 5$ . The baseline dummy is the indicator  $\mathbb{I}\{JZ1977 = 1\}$  that the specificity of the previously held occupation, measured by  $JZ1977$ , is  $JZ1977 = 1$ . The wage penalty after an unemployment spell is increasing in the specificity of the previously held occupation.

In Regression (4),  $\Delta \log wage$  is regressed on the interactions of the occupation-switching indicator  $\mathbb{I}\{occ.switch\}$  with the set of indicators marking the specificity of the previously held occupation, measured by  $JZ1977 = j$  for  $j = 2, 3, 4, 5$ . The wage penalty associated with occupation switching is increasing in the specificity of the previously held occupation (measured by  $JZ1977$ ). Put another way, the wage penalty after an unemployment spell that is increasing in the specificity of the previously held occupation is only observed in occupation switchers. This is consistent with the definition of job zones as an occupation-level measure of the extent of required occupation-specific training. Working in an occupation of a higher job zone means accumulating human capital specific to the occupation. This makes occupation switching more costly, manifesting as a larger wage cut because human capital from the previous occupation is less transferable to a different occupation.

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<sup>16</sup>In the main analysis, the five job zones are aggregated to three groups, low ( $JZ = 1$ ), medium ( $JZ = 2$  or  $3$ ), and high ( $JZ = 4$  or  $5$ ), for presentation purposes; the aggregation does not affect the results.

Finally, Regression (5) adds to Regression (4) the interactions of the employer-switching indicator  $\mathbb{I}\{emp.switch\}$  with the set of indicators marking the specificity of the previously held occupation, measured by  $JZ1977 = j$  for  $j = 2, 3, 4, 5$ .  $\mathbb{I}\{emp.switch\}$  takes a value = 1 when the employer after the unemployment spell is different from the employer before the unemployment spell. Regression (5) confirms that (i) wages cuts after an unemployment spell are due to the loss of occupation-specific capital, not the loss of employer-specific capital, and that (ii) job zones proxy for occupation specificity. Indeed, adding interactions of the  $\mathbb{I}\{emp.switch\}$  does not affect the results of Regression (4). That is, wage cuts after an unemployment spell, observed among only occupation switchers and larger the more specific the previous occupation, are not affected by whether the worker switched employers after the unemployment spell. Workers who switched employers after the unemployment spell do not face wage cuts as long as they do not change occupation, retaining their occupation-specific capital. Workers face wage cuts only if they change occupations. The wage cuts become larger if they had previously worked in a more specific occupation because their human capital, which is specific to their previous occupation, is lost during the occupation switch.

$$\Delta \log wage_{it} = \alpha_1 + \epsilon_{it} \quad (\text{B.1})$$

$$\Delta \log wage_{it} = \alpha_1 + \beta_1 \mathbb{I}\{occ.switch\}_{it} + \epsilon_{it} \quad (\text{B.2})$$

$$\Delta \log wage_{it} = \alpha_1 + \sum_{j=2}^5 \alpha_j \mathbb{I}\{JZ1977_{it} = j\}_{it} + \epsilon_{it} \quad (\text{B.3})$$

$$\begin{aligned} \Delta \log wage_{it} = & \alpha_1 + \sum_{j=2}^5 \alpha_j \mathbb{I}\{JZ1977_{it} = j\}_{it} \\ & + \beta_1 \mathbb{I}\{occ.switch\}_{it} + \sum_{j=2}^5 \beta_j \mathbb{I}\{JZ1977_{it} = j\}_{it} \mathbb{I}\{occ.switch\}_{it} + \epsilon_{it} \end{aligned} \quad (\text{B.4})$$

$$\begin{aligned} \Delta \log wage_{it} = & \alpha_1 + \sum_{j=2}^5 \alpha_j \mathbb{I}\{JZ1977_{it} = j\}_{it} \\ & + \beta_1 \mathbb{I}\{occ.switch\}_{it} + \sum_{j=2}^5 \beta_j \mathbb{I}\{JZ1977_{it} = j\}_{it} \mathbb{I}\{occ.switch\}_{it} \\ & + \gamma_1 \mathbb{I}\{emp.switch\}_{it} + \sum_{j=2}^5 \gamma_j \mathbb{I}\{JZ1977_{it} = j\}_{it} \mathbb{I}\{emp.switch\}_{it} + \epsilon_{it} \end{aligned} \quad (\text{B.5})$$

Table 11: Wage penalty from switching occupations and employers

	(1)	(2)	(3)	(4)	(5)
	$\Delta \log wage$	$\Delta \log wage$	$\Delta \log wage$	$\Delta \log wage$	$\Delta \log wage$
<i>Constant</i>	-0.073*** (0.005)	-0.029*** (0.007)	-0.019** (0.008)	-0.014 (0.010)	-0.009 (0.013)
$\mathbb{I}\{occ.switch\}$		-0.066*** (0.010)		-0.007 (0.015)	-0.004 (0.017)
$\mathbb{I}\{JZ1977 = 2\}$			-0.051*** (0.012)	0.006 (0.019)	0.022 (0.024)
$\mathbb{I}\{JZ1977 = 3\}$			-0.123*** (0.014)	-0.056*** (0.018)	-0.008 (0.026)
$\mathbb{I}\{JZ1977 = 4\}$			-0.103*** (0.020)	-0.015 (0.026)	0.003 (0.039)
$\mathbb{I}\{JZ1977 = 5\}$			-0.316*** (0.099)	-0.267* (0.153)	-0.059 (0.108)
$\mathbb{I}\{JZ1977 = 2\}\mathbb{I}\{occ.switch\}$				-0.082*** (0.025)	-0.076*** (0.028)
$\mathbb{I}\{JZ1977 = 3\}\mathbb{I}\{occ.switch\}$				-0.104*** (0.026)	-0.092*** (0.028)
$\mathbb{I}\{JZ1977 = 4\}\mathbb{I}\{occ.switch\}$				-0.137*** (0.038)	-0.132*** (0.042)
$\mathbb{I}\{JZ1977 = 5\}\mathbb{I}\{occ.switch\}$				-0.112 (0.195)	-0.077 (0.213)
$\mathbb{I}\{emp.switch\}$					-0.008 (0.018)
$\mathbb{I}\{JZ1977 = 2\}\mathbb{I}\{emp.switch\}$					-0.024 (0.031)
$\mathbb{I}\{JZ1977 = 3\}\mathbb{I}\{emp.switch\}$					-0.062* (0.032)
$\mathbb{I}\{JZ1977 = 4\}\mathbb{I}\{emp.switch\}$					-0.024 (0.050)
$\mathbb{I}\{JZ1977 = 5\}\mathbb{I}\{emp.switch\}$					-0.243 (0.205)
<i>N</i>	12495	12495	12495	12495	12495

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Source: SIPP (1985–2013).

Note: By the definition of job zones (JZ) in the DOT/O\*NET of any time period, occupations are rated on a five-point scale with higher values representing higher occupation specificity (longer occupation-specific training).

Regression (1) regresses  $\Delta \log wage$ , the change in log wage after the unemployment spell, on a constant.

Regression (2) regresses  $\Delta \log wage$  on the indicator  $\mathbb{I}\{occ.switch\}$  whether the spell ends in an occupation switch.

Regression (3) regresses  $\Delta \log wage$  on the set of indicators  $\mathbb{I}\{JZ1977 = j\}$  marking the occupation specificity of the previously held occupation, measured by  $JZ1977 = j$  for  $j = 2, 3, 4, 5$  (the baseline dummy is the indicator  $\mathbb{I}\{JZ1977 = 1\}$  that the occupation specificity of the previously held occupation, measured by  $JZ1977$ , is  $JZ1977 = 1$ ).

Regression (4) regresses  $\Delta \log wage$  on the interactions of the occupation-switching indicator with the set of indicators marking the occupation specificity of the previously held occupation, measured by  $JZ1977 = j$ .

Regression (5) regresses  $\Delta \log wage$  on the interactions of the occupation-switching indicator with the set of indicators marking the occupation specificity of the previously held occupation, measured by  $JZ1977 = j$ , and also on the interactions of the employer-switching indicator  $\mathbb{I}\{emp.switch\}$  with the set of indicators marking the occupation specificity of the previously held occupation, measured by  $JZ1977 = j$ .

Standard errors are in parentheses. Longitudinal panel weights are used in all regressions.

Table 12: Examples of occupations that became more specific

JZ1977 → JZ2017	Examples of occupations
JZ1977= 1 → JZ2017= 2	Assemblers of electrical equipment; Hotel clerks; Industrial truck and tractor operators; Payroll and timekeeping clerks
JZ1977= 2 → JZ2017= 3	Bookkeepers and accounting and auditing clerks; Computer and peripheral equipment operators; Licensed practical nurses; Teacher's aides
JZ1977= 3 → JZ2017= 4	Insurance sales occupations; Managers of properties and real estate; Primary school teachers; Technical writers
JZ1977= 4 → JZ2017= 5	Management analysts; Pharmacists; Psychologists; Vocational and educational counselors

## C Additional figures and tables

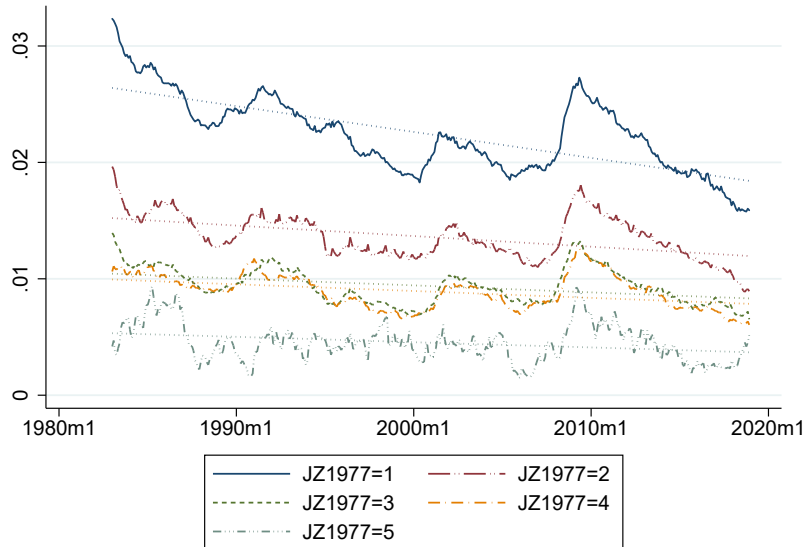


Figure 16: Job separation rate by occupation specificity, with five job zones

Source: Monthly CPS (1983–2018), DOT/O\*NET.

Note: Figure 16 plots the monthly job separation rate (13-week moving average) by occupation specificity (fixed at 1977 SVP rating, aggregated to the five job zones). By the definition of job zones (JZ) in the DOT/O\*NET of any time period, occupations are rated on a five-point scale with higher values representing higher occupation specificity (longer occupation-specific training). The dotted lines are the fitted quadratic trends.

Table 13: Effect of increase in occupation specificity on the job separation rate, with five job zones

	(1)	(2)
	$\mathbb{I}\{EU\} \times 100$	$\mathbb{I}\{EU\} \times 100$
$\mathbb{I}\{JZ1977 = 1\}$	2.569*** (0.015)	5.441*** (0.037)
$\mathbb{I}\{JZ1977 = 1, JZnew > 1\}$	-0.420*** (0.020)	-0.325*** (0.020)
$\mathbb{I}\{JZ1977 = 2\}$	1.656*** (0.012)	4.743*** (0.037)
$\mathbb{I}\{JZ1977 = 2, JZnew > 2\}$	-0.357*** (0.016)	-0.201*** (0.016)
$\mathbb{I}\{JZ1977 = 2, JZnew < 2\}$	0.130*** (0.036)	0.106** (0.036)
$\mathbb{I}\{JZ1977 = 3\}$	1.102*** (0.010)	4.342*** (0.037)
$\mathbb{I}\{JZ1977 = 3, JZnew > 3\}$	-0.262*** (0.012)	-0.035** (0.013)
$\mathbb{I}\{JZ1977 = 3, JZnew < 3\}$	0.847*** (0.029)	0.646*** (0.029)
$\mathbb{I}\{JZ1977 = 4\}$	0.740*** (0.010)	4.243*** (0.040)
$\mathbb{I}\{JZ1977 = 4, JZnew > 4\}$	-0.161*** (0.015)	0.044** (0.015)
$\mathbb{I}\{JZ1977 = 4, JZnew < 4\}$	1.964*** (0.043)	1.400*** (0.044)
$\mathbb{I}\{JZ1977 = 5, JZnew = 5\}$	0.354*** (0.028)	4.217*** (0.050)
Controls	No	Yes
$N$	12299863	12299863

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Source: Monthly CPS (1983-2018), DOT/O\*NET.

Note: By the definition of job zones (JZ) in the DOT/O\*NET of any time period, occupations are rated on a five-point scale with higher values representing higher occupation specificity (longer occupation-specific training). Regressions (1)-(2) regress  $\mathbb{I}\{EU\}$ , the indicator that the worker is employed this month and unemployed the next month, on the set of indicator variables marking the initial occupation specificity  $JZ1977$  of the current occupation, and whether the contemporaneous specificity  $JZnew$  of this previous occupation is higher than its initial occupation specificity ( $\mathbb{I}\{JZ1977 = j, JZnew > j\}$ ) or lower than its initial occupation specificity ( $\mathbb{I}\{JZ1977 = j, JZnew < j\}$ ).

The purpose of the regression is to test whether increasing (decreasing) occupation specificity has a decreasing (increasing) effect on the job separation rate. Negative coefficients in front of  $\mathbb{I}\{JZ1977 = j, JZnew > j\}$  mean that occupations that have become more specific have lower job separation rates than occupations whose occupation specificity have remained the same. Likewise, positive coefficients in front of  $\mathbb{I}\{JZ1977 = j, JZnew < j\}$  indicate the increasing effect of decreasing occupation specificity on the job separation rate.

Regression (2) adds controls: education, age, sex, marital status, race of the worker. Standard errors are in parentheses. Basic monthly weights are used in all regressions.



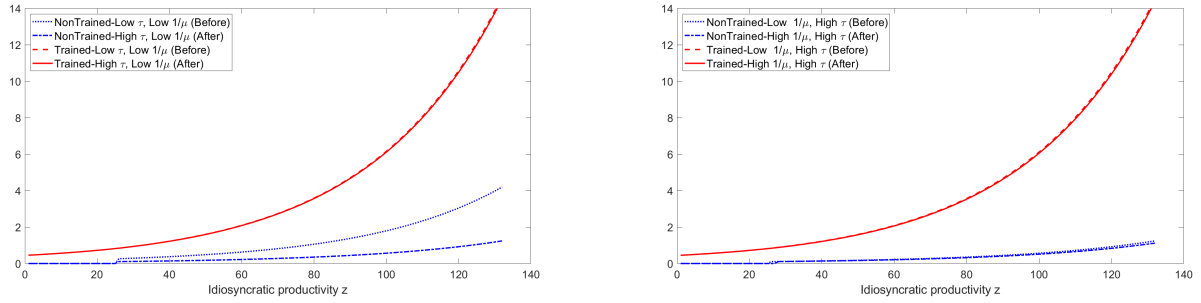


Figure 17: Wage functions of nontrained and trained workers, after increase in  $1/\mu$  or  $\tau$

Note: The left panel plots the wage functions of nontrained and trained workers keeping the average length of occupation-specific training time  $1/\mu = 48$  (“low  $1/\mu$ ”) and changing the output gap between trained and nontrained workers  $\tau = 0.742$  (“low  $\tau$ ,” Before) to  $\tau = 0.943$  (“high  $\tau$ ,” After). The right panel plots the wage functions of nontrained and trained workers keeping  $\tau = 0.943$  (“high  $\tau$ ”) and changing  $1/\mu = 48$  (“low  $1/\mu$ ,” Before) to  $1/\mu = 96$  (“high  $1/\mu$ ,” After). From Table 6, the increase in occupation specificity of initially medium-specific occupations means that  $(\tau, 1/\mu)$  is initially  $(\tau = 0.742, 1/\mu = 48)$  and increases to  $(\tau = 0.943, 1/\mu = 96)$ . Hence the dashed red line and dotted blue line on the left panel would be the wage functions (for trained and nontrained workers respectively) when occupations are initially medium-specific, and the solid red line and long dashed blue line on the right panel would be the wage functions (for trained and nontrained workers respectively) when occupations have become more specific (to high-specific) after being initially medium-specific. The vertical lines are at the reservation productivities.

## D Calibration of occupation specificity parameters

There are two parameters that characterize occupation specificity in the model. One is the average length of occupation-specific training  $1/\mu$ , where  $\mu$  is the exogenous probability each period during employment that a nontrained worker in an occupation becomes a trained worker. The other is the output gap  $\tau$  between trained and nontrained workers in an occupation, where nontrained workers are less productive by a factor of  $(1 - \tau)$  due to the absence of occupation-specific capital. In the model, when occupations become more specific,  $1/\mu$  or  $\tau$  increases. The increase in  $1/\mu$  means that it takes a longer time for nontrained workers in an occupation to acquire the occupation-specific human capital and become trained. The increase in  $\tau$  reflects the increase in the amount of occupation-specific human capital that nontrained workers must acquire to become trained in the occupation.

The increase in occupation specificity in the model must match the increase in occupation specificity in the data. I draw from two data sources to discipline the increase in the occupation specificity parameters  $1/\mu$  and  $\tau$  in the model (independently of job separations, which are the outcomes the model is being asked to explain).

The average length of occupation-specific training  $1/\mu$  is increased according to the definition of job zones (JZ) in the DOT/O\*NET. Over time, starting from 1977, occupations are rated on a five-point scale (JZ = 1 the lowest to JZ = 5 the highest), with higher values representing a longer length of required occupation-specific training. In this paper, JZ1977 or “initial specificity” means the earliest rating of specificity of an occupation (according to the DOT in 1977). To reduce the number of groups (reducing the number of groups does not affect the analysis), I aggregate the five job zones to three levels of occupation specificity (low (JZ = 1), medium (JZ = 2 or 3), and high (JZ = 4 or 5)). If an occupation that was initially nonspecific (JZ1977 = low) becomes more specific (JZnew = medium), the average length of occupation-specific training increases from  $1/\mu = 8$  (weeks) to  $1/\mu = 48$  (weeks). In an occupation that was JZ1977 = medium becomes more specific to JZnew = high, the average length of occupation-specific training increases from  $1/\mu = 24$  (weeks) to  $1/\mu = 96$  (weeks).

The increase in the output gap  $\tau$  between trained and nontrained workers is informed by the increase in the wage loss after an unemployment spell faced by occupation switchers (workers who switch occupation out of unemployment) after an unemployment spell, relative to non-occupation switchers (workers who do not switch occupation out of unemployment) when their previously held occupation has become more specific. I run a regression on pooled observations from the SIPP across the sample period 1985–2013. I collect completed unemployment spells that were initiated by involuntary separations and the following information: change in log wage after the spell (log after wage minus log before wage), the initial specificity JZ1977 and contemporary specificity JZnew (specificity as of the start of the unemployment spell) of the occupation previously held before the spell started, and whether the spell ends with an occupation switch. Again, to reduce the number of groups, the five job zones are aggregated to three levels of occupation specificity (low (JZ = 1), medium (JZ = 2 or 3), and high (JZ = 4 or 5)). I regress the change in log wage

after an unemployment spell on the interactions of the indicator of whether the spell ended with an occupation switch and the set of indicators marking two pieces of information. One is the initial specificity  $JZ_{1977}$  of the occupation previously held before the start of the unemployment spell. The second is whether the contemporary specificity  $JZ_{new}$  of this previous occupation is the same as, higher than, or lower than its initial specificity  $JZ_{1977}$ . For example, an occupation that has become more specific would be occupations that are  $JZ_{1977} = \text{low}$ ,  $JZ_{new} = \text{medium}$  or  $JZ_{1977} = \text{medium}$ ,  $JZ_{new} = \text{high}$ . Education, age, sex, marital status, race of the worker, routine task intensity of the occupation, length of unemployment spell, and their interactions with the occupation-switch dummy are included in the regression as controls. From this regression, I obtain the information listed in Table 14, the average wage change faced by non-occupation switchers and the additional average wage penalty faced by occupation switchers, by the initial specificity ( $JZ_{1977}$ ) of the previously employed occupation and whether the specificity of their previous occupation has increased (contemporary  $JZ_{new}$  is higher than  $JZ_{1977}$ ).

There are several observations from Table 14. The general message of these observations is that occupation-specific human capital is lost when workers switch occupations, manifesting as a wage cut that is not experienced by workers who do not switch occupations. Moreover, the wage loss from switching occupations is greater when the previously held occupation becomes more specific, that is, the loss of occupation-specific capital is greater. First, regardless of the initial specificity of their previously held occupation or whether this previous occupation has become more specific, non-occupation switchers do not face a wage loss. Second, an additional wage penalty is faced by occupation switchers, relative to non-occupation switchers, who previously worked in occupations that were initially specific and have not changed in specificity ( $JZ_{1977} = \text{medium}$ ,  $JZ_{new} = \text{medium}$ ;  $JZ_{1977} = \text{high}$ ,  $JZ_{new} = \text{high}$ ). This stands in contrast to that no additional wage penalty is faced by occupation switchers, relative to non-occupation switchers, who were previously employed in occupations that were initially nonspecific and remained nonspecific ( $JZ_{1977} = \text{low}$ ,  $JZ_{new} = \text{low}$ ). However, if the previous occupation was initially nonspecific and has become more specific ( $JZ_{1977} = \text{low}$ ,  $JZ_{new} = \text{medium}$ ), occupation switchers face an additional wage penalty of 5.4 p.p., relative to non-occupation switchers. As a hypothetical example, sales counter clerks and payroll clerks were both initially nonspecific at the start of the sample period; then in 2003, sales counter clerks remained nonspecific ( $JZ_{1977} = \text{low}$ ,  $JZ_{new} = \text{low}$ ), while payroll clerks have become more specific ( $JZ_{1977} = \text{low}$ ,  $JZ_{new} = \text{medium}$ ). Among those who previously worked in occupations like payroll clerks, occupation switchers face on average 5.4 p.p. larger wage loss relative to the non-occupation switchers. This is not observed for workers who previously worked in occupations like sales counter clerks, where occupation switchers do not face an additional wage penalty relative to non-occupation switchers because there is no occupation-specific capital to be lost after switching occupations.

Table 14: Additional wage penalties faced by occupation switchers after occupations become more specific, by initial specificity

JZ1977 = low, JZnew = low	JZ1977 = low, JZnew = medium	JZ1977 = medium, JZnew = medium	JZ1977 = medium, JZnew = high	JZ1977 = high, JZnew = high	Wage penalty, non-occupation switchers
✓	✓	✓	✓	✓	0.000
JZ1977 = low, JZnew = low	JZ1977 = low, JZnew = medium	JZ1977 = medium, JZnew = medium	JZ1977 = medium, JZnew = high	JZ1977 = high, JZnew = high	Additional wage penalty, occupation switchers
✓	✓	✓	✓	✓	0.000
✓	✓	✓	✓	✓	0.000
✓	✓	✓	✓	✓	-0.054
✓	✓	✓	✓	✓	-0.143
✓	✓	✓	✓	✓	-0.135
✓	✓	✓	✓	✓	-0.176

Source: SIPP (1985–2013).

Note: By the definition of job zones (JZ) in the DOT/O\*NET of any time period, occupations are rated on a five-point scale with higher values representing higher occupation specificity (longer occupation-specific training). To reduce the number of groups, the five job zones are aggregated to three levels of occupation specificity (low (JZ = 1), medium (JZ = 2 or 3), and high (JZ = 4 or 5)). Occupations in low, medium, high job zones require an average length of 8, 12, and 24 weeks of occupation-specific training respectively.

Using pooled observations from the SIPP across the sample period 1985–2013, Table 14 lists the estimated average change in log wage after an unemployment spell faced by non-occupation switchers and the additional wage penalty faced by occupation switchers, by initial specificity (JZ1977) of the previously employed occupation and whether the specificity of their previously held occupation has increased over time (contemporary specificity (JZnew), the specificity as of the start of the unemployment spell, is higher than JZ1977).

The estimates are obtained from the regression of the change in log wage after an unemployment spell on the interactions of the indicator of whether the spell ended with an occupation switch and the set of indicators marking two pieces of information. One is the initial specificity JZ1977 of the occupation previously held before the start of the unemployment spell. The second is whether the contemporary specificity JZnew of this previous occupation is the same as, higher than, or lower than its JZ1977. Education, age, sex, marital status, race of the worker, routine task intensity of the occupation, length of unemployment spell, and their interactions with the occupation-switch dummy are included as controls.

So far, I have discussed the definition of job zones in the DOT/O\*NET and the pooled wage penalty regression estimates from SIPP and mentioned that these two data sources will be informing the two occupation specificity parameters  $1/\mu$  and  $\tau$ . Next, I discuss how the initial steady state is calibrated and how experiments with the model are conducted using these data sources.

### Calibration of initial steady state and experiments conducted

The model is calibrated so that the initial steady state matches the labor market of nonspecific occupations ( $JZ1977 = \text{low}$ ) at the beginning of the CPS sample period, in particular, their 3% job separation rate. This is motivated by my empirical finding that the group of occupations that were initially nonspecific and have become more specific over time accounts for most of the decline in the aggregate job separation rate. After the initial steady state is calibrated, the model is used to predict the decline in job separation rates by initial specificity ( $JZ1977 = \text{low, medium, high}$ ) following the increase in specificity of (all the) occupations. The prediction of these job separation rates by initial specificity is made by simulating the same model after increasing the values of the two occupation specificity parameters (average length of occupation-specific training  $1/\mu$  and output gap  $\tau$ ) accordingly, keeping the remaining parameters at their initial steady-state values. These job separation rates by initial specificity predicted by the model will be compared with the data. They are also then aggregated (using employment shares by occupation specificity at the beginning of the CPS sample period) to obtain the decline in the aggregate job separation rate predicted by the model. The model will also be evaluated by whether it can replicate the empirical finding that the group of occupations that were initially nonspecific and have become more specific is the largest contributor to the decline in the aggregate job separation rate.

The initial steady-state values for the average length of occupation-specific training  $1/\mu$  and output gap  $\tau$  are set as follows.<sup>17</sup> Recall that the initial steady state is to characterize the labor market of nonspecific occupations ( $JZ1977 = \text{low}$ ) at the beginning of the CPS sample period (the beginning of the CPS sample period). First,  $1/\mu$  is set to 8 (weeks), according to the definition of nonspecific ( $JZ = \text{low}$ ) occupations in the DOT/O\*NET. Then given  $1/\mu = 8$ ,  $\tau$  is primarily determined by the zero wage penalty faced by occupation switchers whose previous occupation was initially nonspecific and has remained nonspecific ( $JZ1977 = \text{low}$ ,  $JZ_{\text{new}} = \text{low}$ ) (second line of Table 14). It turns out that the initial steady-state value for  $\tau = 0$ . The zero wage penalty faced by workers (both non-occupation and occupation switchers) whose previous occupation has remained nonspecific throughout the SIPP sample period ( $JZ1977 = \text{low}$ ,  $JZ_{\text{new}} = \text{low}$ ) is interpreted as a labor market characteristic of nonspecific occupations ( $JZ1977 = \text{low}$ ) at the beginning of the CPS sample period. This is consistent with the interpretation of the targeted 3% job separation rate of occupations that are nonspecific ( $JZ1977 = \text{low}$ ) at the beginning of the CPS sample period as the hypothetical job separation rate had these occupations remained nonspecific over time.

After calibrating the initial steady state, the following four experiments are conducted. Each

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<sup>17</sup>The calibration of the initial steady-state values for the remaining parameters is discussed in the main text, Section 3.4.

experiment is conducted by simulating the same model after increasing the values of the two occupation specificity parameters, the output gap  $\tau$  and average length of occupation-specific training  $1/\mu$ , holding the remaining parameters at their initial steady-state values.

The first experiment is to make all the initially nonspecific occupations at the beginning of the CPS sample period more specific ( $JZ_{1977} = \text{low}$ ,  $JZ_{\text{new}} = \text{medium}$ ) and see how the model's predicted job separation rate after this increase in specificity (marked as circled point one in Figure 9 in Section 3.7.1) compares to the actual job separation rate of initially nonspecific ( $JZ_{1977} = \text{low}$ ) occupations at the end of the CPS sample period. First,  $1/\mu$  is increased from 8 to 24 (weeks) according to DOT/O\*NET. Then  $\tau$  is increased from the initial steady-state value  $\tau = 0$  to 0.455 so that together with  $1/\mu = 24$ , the model matches the 5.4 p.p. additional wage penalty faced by occupation switchers, relative to non-occupation switchers, whose previous occupation has become more specific after being initially nonspecific ( $JZ_{1977} = \text{low}$ ,  $JZ_{\text{new}} = \text{medium}$ ) from the pooled SIPP regression (third line of Table 14).

Two points that also apply to the remaining experiments discussed afterward will be clarified. First, the estimated additional wage penalty of 5.4 p.p. faced by occupation switchers, which is used to predict the job separation rate of the initially nonspecific occupations at the end of the CPS sample period after they have become more specific, is from the pooled sample of workers from the SIPP whose previous occupation specificity has increased at different points in time during the SIPP's sample period (1985–2013) after being initially nonspecific. In the data, it is not the case that after being initially nonspecific, occupations remain nonspecific throughout the sample period and become specific only in the final year of the sample period. In other words, in the SIPP data, I interpret all the years after 1983 (the starting year of the SIPP sample) as the post-“occupation-specificity-increase” period and use the average additional wage penalty faced by occupation switchers across all these years to predict the job separation rate at the end of the CPS sample period. Second, when experimenting with the model of the effect of increasing occupation specificity, it is assumed that all the occupations are becoming specific. This is not exactly the case in the data, where some occupations do not change in specificity throughout the entire sample period. For example, from Table 1 in Section 2.2, the transition matrix listing the changes in occupation specificity, 14% of initially nonspecific occupations remain nonspecific by the most recent specificity ( $JZ_{2017}$ ). The reason for making all occupations specific when experimenting with the model is because the model represents the labor market of occupations with the same occupation specificity (same job zone), and these occupations are assumed to be symmetric.

The second experiment is to predict and compare with the data the job separation rate of initially medium-specific ( $JZ_{1977} = \text{medium}$ ) occupations at the beginning of the CPS sample period (marked as circled point two in Figure 9 in Section 3.7.1). First,  $1/\mu$  is set to 24 (weeks) according to DOT/O\*NET. Then,  $\tau$  is set to  $\tau = 0.742$  so that together with  $1/\mu = 24$ , the model matches the 14.3 p.p. additional wage penalty faced by occupation switchers, relative to non-occupation switchers, whose previous occupation is ( $JZ_{1977} = \text{medium}$ ,  $JZ_{\text{new}} = \text{medium}$ ) from the pooled SIPP regression (fourth line of Table 14).

The third experiment makes the initially medium-specific occupations more specific ( $JZ1977 = \text{medium}$ ,  $JZ_{\text{new}} = \text{high}$ ) and predicts their job separation rate (marked as circled point three in Figure 9 in Section 3.7.1). This will be compared to the actual job separation rate of initially medium-specific ( $JZ1977 = \text{medium}$ ) occupations at the end of the CPS sample period. First,  $1/\mu$  is increased to from 24 to 48 (weeks) according to DOT/O\*NET. Then,  $\tau$  is increased from  $\tau = 0.742$  to  $\tau = 0.943$  so that together with  $1/\mu = 48$ , the model matches the 13.5 p.p. additional wage penalty faced by occupation switchers, relative to non-occupation switchers, whose previous occupation is ( $JZ1977 = \text{medium}$ ,  $JZ_{\text{new}} = \text{high}$ ) from the pooled SIPP regression (fifth line of Table 14).

The fourth experiment predicts and compares the job separation rate of initially high-specific ( $JZ1977 = \text{high}$ ) occupations at the beginning of the CPS sample period with the data. Because these occupations are already at their highest level of occupation specificity, this “predicted” job separation rate at the beginning of the CPS sample period is set to be the predicted job separation rate at the end of the CPS sample period as well. Both are marked as circled point four in Figure 9 in Section 3.7.1. First,  $1/\mu$  is set to 48 (weeks) according to DOT/O\*NET. Then,  $\tau$  is set to  $\tau = 0.996$  so that the model matches the 17.6 p.p. wage penalty faced by occupation switchers, relative to non-occupation switchers, whose previous occupation is ( $JZ1977 = \text{high}$ ,  $JZ_{\text{new}} = \text{high}$ ) from the pooled SIPP regression (sixth line of Table 14).

The values for  $1/\mu$  and  $\tau$  under the initial steady state and the four experiments discussed above are listed in Table 6 in Section 3.5 in the main text.

From the SIPP pooled regression, when occupations become more specific, occupations switchers face a larger wage penalty due to the larger loss in occupation-specific capital. The pattern observed from Table 6 is that after the increase in average occupation-specific training  $1/\mu$  according to the DOT/O\*NET, the output gap  $\tau$  must be increased for the model to produce this increase in wage penalty faced by occupation switchers following the increase in occupation specificity. There are two reasons why the increase in  $\tau$  is needed with the increase in  $1/\mu$ . First, when  $1/\mu$  increases, holding  $\tau$  fixed, a larger share of the occupation switchers would be workers who are nontrained in their previous occupation. It becomes more likely that nontrained workers will become unemployed before the opportunity arrives to become trained (this opportunity arrives later because of the increase in  $1/\mu$ ), and then they will be hit by the exogenous occupation-switching shock. The average wage loss associated with occupation switching comes from the occupation switchers who were trained in their previous occupation and earned higher wages than nontrained workers. Higher  $1/\mu$  reduces the share of trained workers among occupation switchers and hence makes the average change in wages after occupation switching less negative. Second, when  $1/\mu$  increases, there is an increase in matches with trained workers with lower idiosyncratic productivity  $z$ . This is shown in the left panel of Figure 7, where the increase in  $1/\mu$  lowers the reservation productivity of trained workers; the reservation productivity of nontrained workers is not affected much. Hence given  $\tau$ , the increase in  $1/\mu$  lowers the average wage of trained workers, which in turn will dampen the average wage loss faced by occupation switchers who were trained workers and, therefore, reduce the overall

average wage loss associated with occupation switching. For these two reasons, when  $1/\mu$  increases,  $\tau$  must be increased even more, to not only offset the decreasing effect that higher  $1/\mu$  has on the average wage penalty faced by occupation switchers but also to match the fact that the average wage penalty faced by occupation switchers becomes even larger when the previous occupation becomes more specific ( $1/\mu$  becomes higher).



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