Sectoral Differences in Matching Technology

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Abstract

This paper estimates Cobb-Douglas matching functions for four sectors of the US labor market—production, sales, professional, and services—while allowing the search effort to vary across worker types and the matching functions to display increasing or decreasing returns to scale. We find that (a) returns to scale in the production, sales, and service sectors are close to constant while the returns to scale in professional sector is increasing, (b) vacancy elasticity is substantially higher in the professional sector than in other sectors, (c) unemployment elasticity is substantially higher than the vacancy elasticity in all sectors, and (d) baseline matching efficiency is the highest in the production sector than in other sectors.

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1 Introduction

Over the last two decades, there has been a significant heterogeneity in movements in the number of unemployed workers and vacancies across different sectors of the US economy. For example, during the Great Recession, the increase in the number of unemployed workers was more pronounced in the production sector than in other sectors. In contrast, during the COVID-19 Recession, the surge in the number of unemployed workers was concentrated in the services sector (Figure 1a). Over the same period, the number of vacancies increased by three million in the services sector while only increasing by a million in the production sector (Figure 1b).

Meanwhile, there has not been a lot of research on how the matching technology between unemployed workers and vacancies differs across sectors. Research on the labor market typically features a constant returns to scale aggregate matching function that does not distinguish between unemployment (or vacancies) in one sector versus another. Even when sectors are explicitly modeled, the unemployment elasticity and the vacancy elasticity are assumed to be the same across sectors (Şahin et al., 2014; Barnichon and Figura, 2015), although there isn't an obvious reason why the matching function in different sectors would have the same elasticities.

In light of these observations, we estimate Cobb-Douglas matching functions for four sectors of the US labor market—production, sales, professional, and services—while allowing the search effort to vary across worker types and the matching functions to display increasing or decreasing returns to scale. We first estimate Cox hazard model with distinct base hazards by industry to estimate the individual search effort parameters. Next, we estimate the unemployment elasticity, vacancy elasticity, and matching efficiency in each sector while controlling for worker types.

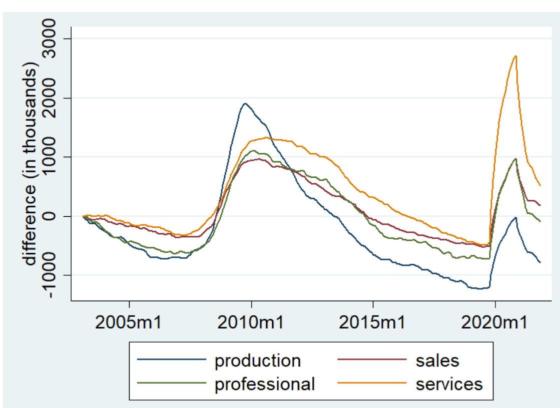
We find that the elasticities and the matching efficiency parameters are significantly different across sectors. The vacancy elasticity is higher in the professional sector (0.53) than in any other sector (0.27-0.34). The unemployment elasticity is lower in the sales sector (0.67) than in any other sector (0.81-0.86). The matching efficiency is higher in the production sector (0.34) than in any other sector (0.22-0.25). The results imply that policies aimed at increasing the search effort of unemployed workers or increasing the number of job openings may be more effective in some sectors than others.

We also find that the matching function displays constant returns to scale only in the sales sector. The matching function in the production sector, the professional sector, and the services sector display increasing returns to scale. Since worker productivity is likely to be more homogeneous in the sales sector where the tasks are more routine, this is consistent with a theoretical result in Gan and Li (2016) that the matching function will display increasing returns to scale in a labor market where both workers and firms have heterogeneous productivity.

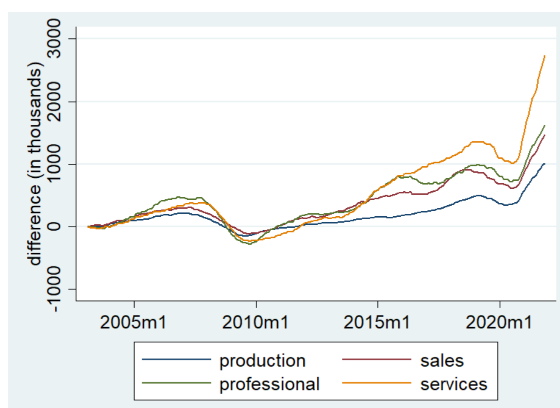
This paper is organized in the following way. Section 2 reviews related literature. Section 3 describes the data and how we define the main variables. Section 4 describes the estimation procedure. Section 5 reports the estimation results. Section 6 concludes.

Figure 1: Level Changes from January, 2003

(a) Unemployed Workers



(b) Vacancies



Notes: (1) The production sector includes NAICS industries “mining and logging", “construction", “non-durable goods manufacturing", and “durable goods manufacturing". The services sector includes NAICS industries “healthcare and social assistance", “arts, entertainment, and recreation", “accomodation and food services", and “other services". (2) Unemployment and vacancies are uniformly weighted moving averages using a 1-year window (6 months lag, current month, 6 months forward).

Source: Current Population Survey.

2 Related Literature

This paper builds on the literature that estimates job matching functions while taking into account worker heterogeneity. Krueger and Mueller (2010) and Krueger et al. (2011) provide empirical evidence that time spent on job search depends worker characteristics such as US benefit eligibility and spell of unemployment. Barnichon and Figura (2015) and Hall and Schulhofer-Wohl (2018) argue that the share of workers with low search effort in the unemployment pool went up considerably during the Great Recession and caused a decline in the job finding rate. Abraham et al. (2020) develops a measure of labor market tightness taking into account worker heterogeneity in search effort. This paper closely follows Barnichon and Figura (2015) in modeling worker heterogeneity. But unlike Barnichon and Figura (2015), this paper allows the matching function to display increasing or decreasing returns to scale and allows the unemployment elasticity and the vacancy elasticity to differ across sectors.

This paper belongs to the literature that assesses the constant returns to scale (CRS) assumption in the Cobb-Douglas job matching function. Petrongolo and Pissarides (2001) provides a comprehensive overview of papers published in 2000 or before that test the CRS assumption. The results are mixed: Of the fifteen papers that test the CRS assumption, six reject the CRS assumption at five percent significance level, nine do not. Kangasharju et al. (2005) estimates the returns to scale using Finnish panel data and finds that the Cobb-Douglas specification exhibits constant returns to scale while the translog specification exhibits increasing returns to scale. This paper is close in spirit to Fahr and Sunde (2004), which estimates the Cobb-Douglas job matching function in different occupation groups in Germany without assuming constant returns to scale. They find that different occupations seem to exhibit fundamentally different labor market structures—with some occupations displaying increasing returns to scale and others displaying decreasing returns to scale.

This paper is also related to the literature that studies how sectoral shifts affect the unemployment rate. Ever since Lilien (1982) argued in his seminal work that sectoral shifts accounted for more than half of all cyclical variation in unemployment between 1948 and 1980, numerous papers—both theoretical (Rogerson, 1987; Hosios, 1994) and empirical (Loungani and Rogerson, 1989; Brainard and Cutler, 1993; Valletta and Kuang, 2010)—have investigated how sectoral shifts affect the unemployment rate by making it harder for unemployed workers to find new employment in the sectors they used to work in. More recently, Şahin et al. (2014) argued that mismatch between vacancies and unemployment across sectors accounted for a third of the increase in the unemployment rate during the Great Recession. This paper complements the literature by highlighting a new channel through which sectoral shifts can affect the job finding rate. If sectors with low unemployment elasticity of matching are shrinking (thus have high unemployment) and sectors with low vacancy elasticity of matching are expanding (thus have many vacancies), the job finding rate will tend to be lower than predicted by aggregate unemployment and aggregate vacancies.

3 Data

We use matched monthly data from the Current Population Survey (CPS) and Job Opening and Labor Turnover Survey (JOLTS) covering January 2003 to Dec 2021. Using CPS data allows us to calculate monthly labor market transitions for workers with different characteristics (duration of unemployment, reason for unemployment, and demographics) in different industries. Using JOLTS data allows us to track monthly vacancies by industry. We start our sample period in Jan 2003 because the industry code in CPS changed between Dec 2002 and Jan 2003.

CPS data reference the week that contains the 12th while JOLTS vacancy data reference the last day of the month. To align CPS data with JOLTS data, we use the following definitions; U_t denotes the number of unemployed workers in CPS in month $t-1$, m_t denotes the number of unemployed workers in CPS in month $t-1$ who were employed in month t, and V_t denotes the number of vacancies in JOLTS in month $t-1$.

Following Barnichon and Figura (2015). We divide the US labor market into four sectors: production, sales, professional, and services. CPS industries are coded in Census codes and JOLTS industries are coded in NAICS codes. The following table describes how the industry codes are mapped to the four sectors.

Table 1: Sectors

Sector	NAICS Major Industry	Census Industry
production	mining and logging	270, 370-490
	construction	770
	nondurable goods manufacturing	1070-2390
	durable goods manufacturing	2470-3990
sales	wholesale trade	4070-4590
	retail trade	4670-5790
	transportation, warehousing, utilities	6070-6390
professional	information	6470-6780
	finance and insurance	6870-6992
	real estate, rental, leasing	7071-7190
	professional and business services	7270-7790
	educational services	7860-7890
services	healthcare, social assistance	7970-8470
	arts, entertainment, recreation	8561-8590
	accommodation, food services	8660-8690
	other services	8770-9290

To minimize the effects of spurious labor market transitions, we restrict the definition of “job finding" to being employed for at least two consecutive months, following the literature(Rothstein, 2011; Valletta, 2014; Farber et al., 2015; Petrosky-Nadeau and Valletta, 2021; Farber and Valletta, 2015). We select individuals that are unemployed at a given month $t-1$ and are observed for two consecutive months (t and $t+1$) afterwards. If the individual is employed in months t and $t+1$, then the individual's job finding status is 1. If not, then the individual's job finding status is 0.

4 Model Specification and Estimation Methods

In this section, we describe our estimation procedure to estimate the matching function with sector specific matching technologies. To estimate our continuous time matching function using discrete data only with monthly frequency, we assume that during the interval between time t and $t+1$, denoted period t, the instantaneous flow of new hires in sector i is constant.

The number of new hires (m) and the job finding probability (f) in sector i at period t are given by

$$m_{it} = \mu_i (U_{it})^{\beta_i} V_{it}^{\alpha_i} \tag{1}$$
$$f_{it} = \frac{m_{it}}{U_{it}}, \tag{2}$$

where U_{it} denotes the number of unemployed workers in sector i at time t and V_{it} denotes the number of vacancies in sector i at time t.

Based on the matching technology in equation 1, the expected job finding rate for an individual j in segment i at time t is given as

$$f_{jit} = \frac{s_{jit}}{s_{it}} \frac{m_{it}}{U_{it}} = \mu_i \frac{s_{jit}}{s_{it}} (U_{it})^{\beta_i - 1} V_{it}^{\alpha_i}, \tag{3}$$

where s_{it} represents the average search efficiency in sector i at time t, and s_{jit} indicates individual j's search efficiency in sector i and time t. The individual search efficiency is estimated using the Cox hazard of the following form:

$$s_{jit} = s_{0it} e^{(\gamma X_{jt})}. \tag{4}$$

s_{jit} represents the individual search efficiency, which is the unemployment exit hazard rate for individual j in sector i and during unemployment week t. s_{0it} is a baseline hazard specific to each sector i, and X_{jt} denotes observable individual characteristics.

The set of controls X_{jt} includes state and year-specific effects, indicators for economic recession, the average state unemployment benefits[1], age, gender, education, and dummies for four reasons for unemployment: permanent layoff, temporary layoff, re-entering the labor force, and quitting the job. The coefficients are assumed to be constant across all industry groups, while the baseline hazard can vary depending on the group. Therefore, the estimates of γ account for the heterogeneity that arises in the matching probability from individual characteristics rather than sector-specific labor market conditions.

In the second stage, we use the estimated parameters on the worker characteristics γ to measure relative search efficiency as $\frac{s_{jit}}{s_{it}}$, and then estimate the remaining matching function parameters from the individual job-finding probability over the period t using the equation below:

$$F_{jit} = 1 - e^{-\mu_i \frac{s_{jit}}{s_{it}} f_{it}} = 1 - e^{-\mu_i s_{jit} (U_{it})^{\beta_i - 1} V_{it}^{\alpha_i}}. \tag{5}$$

We use the maximum likelihood method to estimate the sector-specific matching efficiency μ_i and the matching function elasticities α_i and β_i.

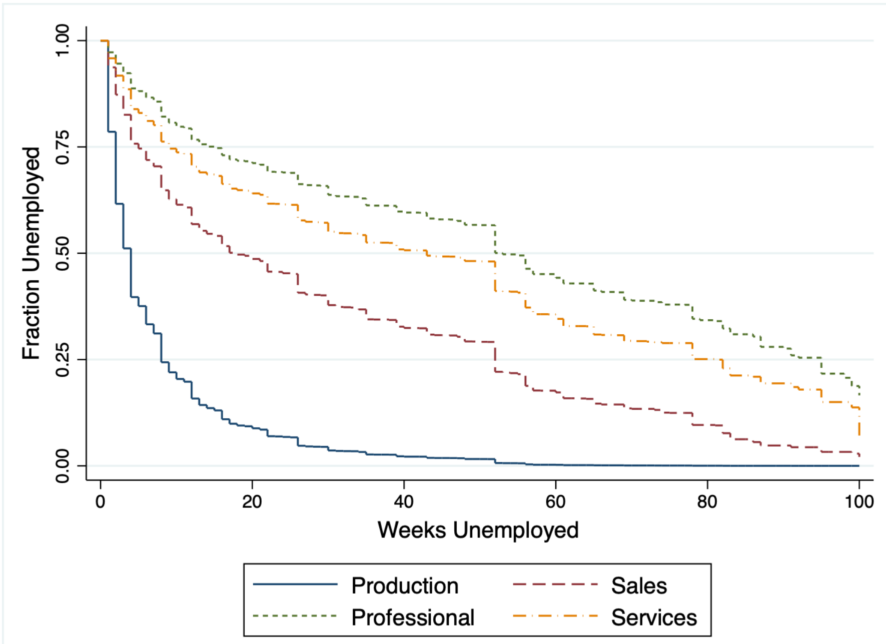
From the CPS data we observe whether each individual j in sector i is hired or staying unemployed in period t. Denoting $y_{jit} = \{1, 0\}$ the job search outcome, where $y_{jit} = 1$ if an individual j finds a job and $y_{jit} = 0$ if an individual j stays unemployed, the log-likelihood function $l(\theta)$ is given by

$$l(\theta) = \sum_{t=1}^{T} \sum_{i=1}^{I} \sum_{j=1}^{J_i} [y_{jit} \ln(1 - F_{jit}) + (1 - y_{jit}) \ln F_{jit}], \tag{6}$$

where J_i is the number of individuals in segment i. We estimate the parameters θ by minimizing $l(\theta)$.

[1] The average state unemployment benefits are obtained from the Department of Labor. (https://oui.doleta.gov/unemploy/claimssum.asp)

Figure 2: Estimated Survival Curves by Industry



Notes: Kaplan-Meier survival curves by industry with (a) and without (b) controls for individual characteristics. The controls consists of the monthly average unemployment benefits by state, recession indicator, age, gender, education, state and year specific effects, and reasons for unemployment.

5 Estimation Results

5.1 Determinants for Search Efficiency

Figure 2 shows the Kaplan-Meier survival curves by industry with and without controls for observable individual characteristics. The estimated survival curves suggests that observable characteristics play a crucial role in unemployment exits, highlighting the significance of accounting for the heterogeneity of unemployment pools across sectors when estimating sectoral matching functions.

After accounting for the heterogeneity in unemployment pools, the workers in the production sector exit unemployment at the fastest rate, followed by workers in the sales, services, and professional sectors in that order.

Table 2 reports the coefficients from the first stage estimation of the Cox Hazard Model in equation 4. These estimates imply the importance of each observable characteristic on job matching probability, and show the effects of a percentage increase or decrease in job matching probability within the same industry.

The most significant explanatory variable for heterogeneous matching probability within a sector is the reason for unemployment. The job matching probability for those who are temporarily laid off is 1.5 times higher than that for those who are permanently laid off. Those who quit and re-entered the labor market are also more likely to find a new job compared to those who were permanently laid off, with rates of 42.2% and 12.7%, respectively.

Not surprisingly, workers are less likely to find a job as they are older, and the job matching probability for female workers 5% less than male workers. Finally the job finding rates go up with the education level.

5.2 Coefficients for Sectoral Matching Function

Table 3 reports the coefficient estimates of the matching function with sector-specific parameters, α_i, β_i, and μ_i. The results suggest that there is significant heterogeneity in the matching technology over the four different sectors. The vacancy elasticity α_i and the unemployment elasticity β_i represent how sensitively the number of matches response to the numbers of job openings and job seekers respectively, showing relative importance of these two factors on the number of new matches.

In the literature, matching functions are often assumed to be a constant returns to scale (CRS) Cobb-Douglas function, that is, the sum of the two coefficients α_i and β_i is often assumed to be 1. $\alpha_i + \beta_i > 1$ implies increasing returns to scale (IRS), meaning that higher numbers of job seekers and vacancies increase new matches in a greater proportion. Similarly, $\alpha_i + \beta_i < 1$ implies decreasing returns to scale (DRS) of the matching function.

μ in an aggregate matching function is typically assumed to be time-varying, and the time-varying μ represents the levels of matching efficiency at the time, which is not

Table 2: Determinants of Search Efficiency: Cox Hazard Model Estimates

	Coefficient	Std. err.
Age	-0.054	0.002
Age squared	0.0004	0.00002
Female	0.050	0.008
Education		
High school	0.022	0.010
College	0.167	0.013
Reason for unemployment		
Temporary layoff	1.511	0.010
Re-entry	0.127	0.011
Quit	0.422	0.013
State and year fixed effects	x	

Notes: Coefficients reported are elasticities of hazard rate with distinct base hazard for each sector, production, sales, professional, and services. Education coefficients are relative effects compared to 'less than high school degree', and Reasons for unemployment coefficients are relative to 'permanent layoff'. The samples include 262,994 panels from 2003 to 2022.

Table 3: Estimates of the Matching Function Parameters

	(1)	(2)	(3)	(4)
Sector	Production	Sales	Professional	Services
α_i (Vacancy elasticity)	0.260	0.313	0.487	0.297
	(0.008)	(0.020)	(0.020)	(0.013)
β_i (Unemployment elasticity)	0.774	0.698	0.894	0.751
	(0.017)	(0.018)	(0.027)	(0.021)
μ_i (Sectoral matching efficiency)	0.434	0.311	0.312	0.314
	(0.005)	(0.004)	(0.002)	(0.006)
Observations	69,278	53,505	67,247	73,462

Notes: Standard errors are reported in parentheses. Each column reports parameter estimates for the sector-specific matching technology.

explained by the observed size of unemployment and vacancy at the time period. In that case, μ is the regression residual in a standard matching function. In our model, μ_i is assumed to be constant over time and varies across sectors. This sector-specific μ_i represents the average matching efficiency of each sector over entire time horizon.

Row 1 of Table 3 reports the vacancy elasticity, α_i, for each sector. The vacancy elasticity is substantially higher in the professional sector (0.487) compared to all other sectors, which ranged from 0.260 to 0.313. This means that as more vacancies open up, the number of new matches will increase at the fastest rate in the professional sector.

The unemployment elasticity ranges from 0.698 (sales) to 0.894 (professional), and is substantially higher than the vacancy elasticity in all four sectors. This result is consistent with previous studies that estimated aggregate matching functions (Petrongolo and Pissarides (2001)). The unemployment elasticity is lowest in the sales sector, meaning that the number of new matches will increase at the slowest rate in the sales sector as more people look for new jobs.

Based on the estimates of α_i and β_i in Table 3, the matching function is close to CRS technology in production, sales, and service sectors. The sum of vacancy and unemployment elasticity, α_i and β_i, is 1.011 in the sales sector, and it is 1.034 and 1.048 in the production and services sector, respectively. The degree of increasing returns is largest in the professional sector, as the sum of the elasticity of vacancy and unemployment is 1.381, substantially higher than 1. The sector-specific matching efficiency μ_i in the production sector, 0.434, is considerably higher than in any other sectors, which range from 0.311 to 0.314. μ_i measures the average matching efficiency of each sector over the entire time period, and the estimates of μ_i suggest that with the same numbers of job seekers and job openings, the number of matches will be the greatest in the production sector.

The results in Table 3 show that strong heterogeneity in matching technology may exist across the four distinct sectors. They suggest that changes in the sectoral shares in the unemployment or in vacancy will be important when predicting the number of matches and aggregate job-finding probability.

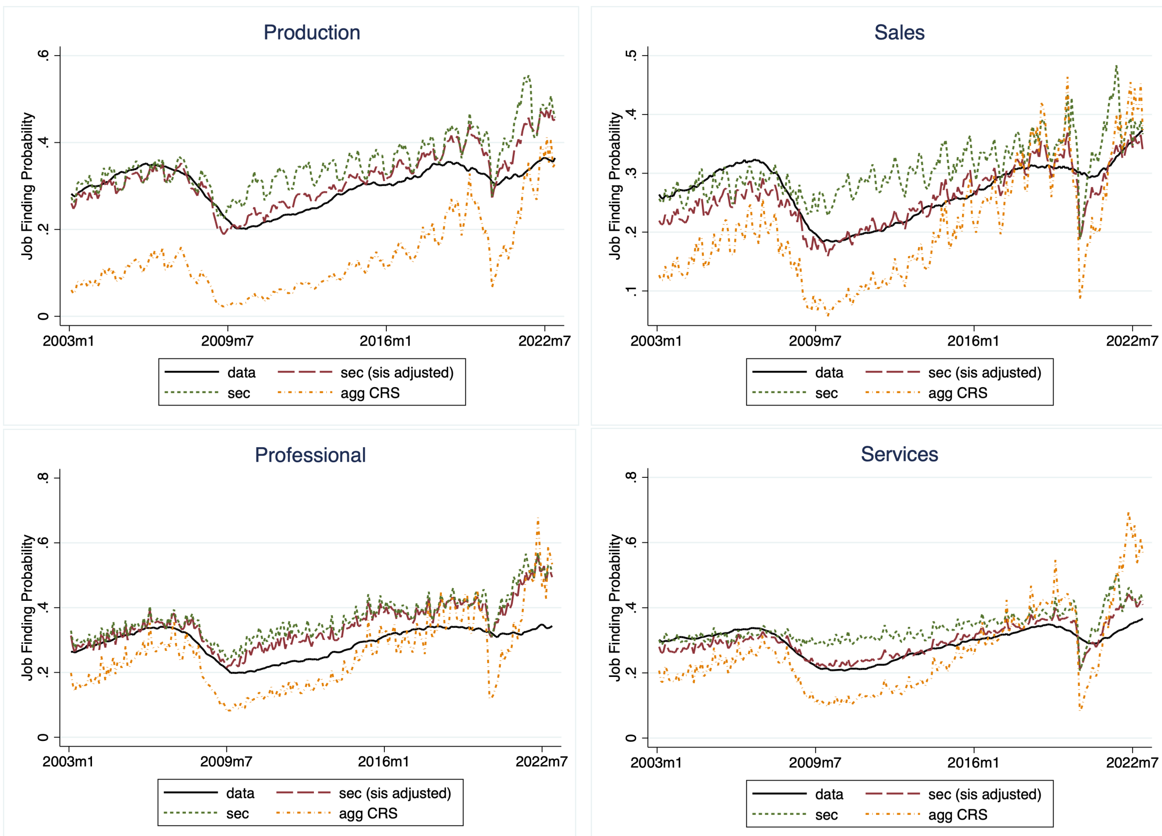
5.3 Sectoral Job Finding Rates

Using the estimated coefficients, we evaluate whether our sectoral matching function can predict the empirical job finding rate, and we compare our model with a typical CRS aggregate matching function.

Figure 3 plots the empirical job finding rates of each sector from the Current Population Survey (CPS) data and their predicted values from the sectoral and CRS aggregate matching function from 2003 to 2022.

In all four sectors, the job finding rates display procyclical movements as they significantly decline during the recessions. From the end of 2007 to the early 2010, the job finding rate in the production sector fell sharply by 12.7 percentage points. All other sectors experienced profound downturns in the job finding rates during the time although the effects were not as large as in the production sector. During the COVID-19 recession, on the other hand, job finding rate fell most severely in Services sector.

Figure 3: Job Finding Rates by Sector



Notes: a) Empirical job finding rates are from CPS data over 2003-2022. The data job finding rates are the four-quarter moving averages. b) Job finding rate predicted by the sectoral matching function with and without controls for heterogeneous unemployment pools, using the parameter estimates from the table 3. c)Job finding rate predicted by CRS aggregate matching function. The conventional CRS matching elasticities are estimated by MLE. Estimates for vacancy elasticity and the matching efficiency are 0.229 and 0.300, respectively.

One well-known trend in job finding rate in the United States is the dramatic decline in matching efficiency, which is the regression residuals in the CRS aggregate matching function, after 2008 crisis through 2015. That is, the difference between the actual and predicted job finding rates fell sharply during the 2008 crisis and it persisted for several years after the recession. This pattern is clearly shown in residuals from the CRS aggregate matching function. In particular, the positive residuals before 2008 crisis is largely driven by a gap between the empirical and predicted job finding rates in the production sector. And unprecedented falls in the residuals were followed in all four sectors after the recession.

Using the sectoral matching function, however, the residuals are much smaller across all periods in all four sectors. The sector-specific matching function can more precisely predict the job finding rate in each sector. And the puzzling pattern of regression residuals, which was often interpreted as time-specific matching efficiency, is mostly explained by the sectoral difference in matching function, unemployment and vacancies.

6 Conclusion

This paper provides an empirical analysis of worker-job matching over four sectors in the US labor market. We estimate a matching function with sector specific matching efficiency and elasticity, while allowing the matching technology in each sector to take a form of constant, decreasing, or increasing Cobb-Douglas function. The empirical results show that there exist significant heterogeneity in matching technologies over the four distinct sectors. In particular, the average matching efficiency is highest in production sector, and the matching technology in professional sector displays increasing returns to scale while all the other sectors are closer to constant returns. Relative size of vacancy and unemployment elasticity also differs significantly by sector. These findings suggest that it is important to account for the size of sectoral unemployment and vacancy when evaluating the aggregate number matches and job finding rate.

The sectoral analysis enables us to see a closer look at the movements of matching efficiency over time. The significant fall in residuals from the CRS aggregate matching function over 2008 to 2015 period was mostly driven by the disappearance of large residuals which was prevailing prior to 2008 in the production sector. Our sectoral matching function can successfully capture the movements of job finding rates in all four sectors over 2003 to 2021.

As with many existing studies on matching, our empirical analysis relies on the assumption that there is no interaction across distinct sectors. Under this assumption, the unemployed find a match only within the sector they were previously in, and the sectoral unemployment level may not precisely represent the number of individuals who are searching for a job in the sector. An important direction for future study is to incorporate job seekers' decisions of job mobility and link the job matching process with this endogenous choice by workers.

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