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DISCUSSION PAPER SERIES

IZA DP No. 15610

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ABSTRACT

Matching Efficiency and Heterogeneous Workers in the UK*

The matching efficiency of the standard matching function is known to follow a pro-cyclical pattern. An observed rightward shift in the UK's Beveridge Curve after the Great Recession, suggests a decrease in the matching efficiency between vacancies and unemployed workers. This paper studies the changes in the labour market's efficiency over the period between 2001 and 2015 in the UK, and decomposes various factors behind it, such as industrial labour market segmentation and characteristics of unemployed, using the standard aggregate matching function. Consistent with the findings for the US (Barnichon and Figura (2015), Hall and Schulhofer-Wohl (2018)), I find that the UK labour market experienced a decrease in the matching efficiency during the Great Recession. However, contrary to what Barnichon & Figura (2015) observed in the US, composition of the labour market did not account for much of this decrease, leaving labour market tightness as the main factor for the decline in efficiency in matching unemployed workers and available vacancies. Accounting for labour market segmentation and worker heterogeneity, can explain 24% of movements in the matching efficiency over the period between 2001Q3 and 2014Q3.

JEL Classification: J6, J41, J42
Keywords: unemployment, mismatch, matching efficiency

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1 Introduction

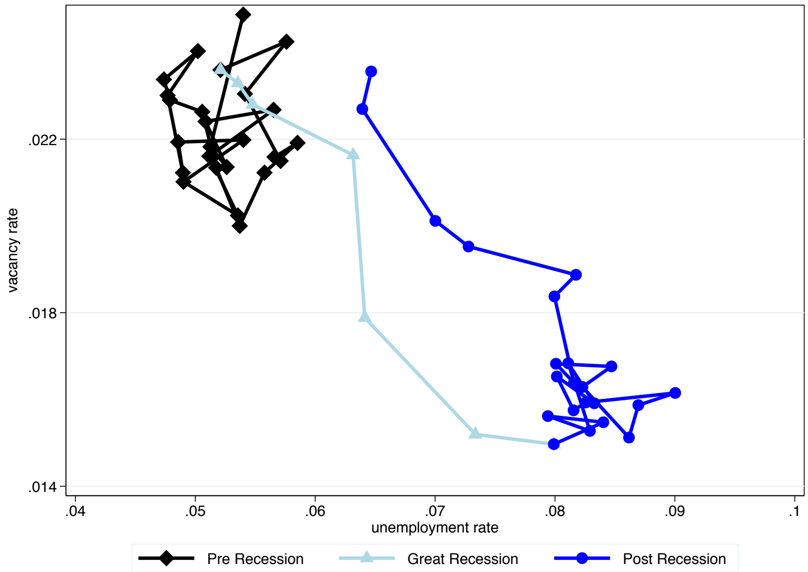

Figure 1: The Beveridge Curve
Source: Labour Force Survey, Vacancy Survey and author's calculations.

The standard matching function, as set by the Diamond-Mortensen-Pissarides model, did a good job at predicting the job finding rate for many years and different economies. The topics on the pro-cyclical behaviour of the rate at which people find suitable vacancies has been a well explored topic in the search and matching literature[1]. It has been found that the matching efficiency of an aggregate matching function also follows a pro-cyclical pattern (Bowlus (1995), Klinger and Rothe (2012)), showing that the same number of searchers yield more matches in a boom rather than a recession. This paper examines the extent to which this pattern might be driven by the composition of the unemployed workers in the UK before and after the Great Recession.

The main question of this paper is whether composition of unemployed workers affects the matching function in the UK over the period between 2001Q3 and 2014Q3, i.e., is there mismatch between vacancies and unemployed workers, how does it differ in different industries of the labour market, and whether changes in unemployment pool have any effect on the matching mechanism and outcomes.

Although the rate to which unemployment increased during the Great Recession is much lower than during the previous economic crises in the UK, it received a lot of attention from labour economists as the recovery process was particularly long and therefore,

[1] See Shimer (2005b); Fujita and Ramey (2009); Gomes (2012); Barnichon and Figura (2015).

costly. The standard model of search and matching assumes a stable relation between number of matches and the fluctuation of unemployment and vacancies ratio, which is otherwise known as labour market tightness. In a frictional labour market, the matching function is assumed to be

$$m = f(U, V),$$

where m, U and V is number of matches, number of unemployed workers and vacancies, respectively. The majority of research on the effect of the Great Recession on labour market outcomes was done for the US market. It was found that one of the most important factors that prevented unemployment rate from an efficient recovery is a sharp decline in job finding probability conditional on labour demand and supply (Sahin et al. (2014)).

Figure 1 plots unemployment rate against vacancy rate in the UK for the period between 2001 and 2015. This relationship is referred to as the Beveridge Curve, which typically shows a negative relationship between vacancies and unemployment (Blanchard and Diamond (1989)). The Beveridge Curve is used to distinguish between cyclical and structural changes in the labour market. The movement along the Beveridge Curve represents the cyclical changes, while shifts of the curve show structural changes in the labour market. The rightward shift of the Beveridge Curve that is observed in Figure 1 is the result of an increased unemployment level for a given number of vacancies. This suggests that the efficiency in matching labour market agents decreased during the Great Recession.

To study the questions in this paper, I employ the aggregate matching function, which takes the number of vacancies and unemployed workers as inputs and gives the number of new matches as its output. Several recent studies (e.g., (Sahin et al., 2014; Barnichon and Figura, 2015; Hall and Schulhofer-Wohl, 2018)) showed that mismatch between vacant jobs and unemployed workers arises because of a decline in average quality of unemployed workers or the fact that they tend to look for jobs in different sectors than available vacancies are. Therefore, to account for worker heterogeneity, I decompose the aggregate matching function to incorporate a number of worker characteristics, such as age, gender or the level of education. I also disaggregate the labour market into sub-markets by industries at 1-digit SIC level.

I examine the performance of the standard matching model in comparison to extended models that account for the composition of the UK labour market. That is, I estimate the aggregate matching function that includes labour market segmentation and worker heterogeneity using the UK micro data.

There is a small but rapidly growing number of papers in the literature in recent years that have focused on matching efficiency and the size of the mismatch (e.g., (Veracierto, 2011; Sahin et al., 2014; Davis et al., 2013; Barnichon and Figura, 2015)). Barnichon and Figura (2015) estimate that although the standard matching function was stable over the period from 1967 to 2007 in the US, it has broken down after 2007. After explicitly incorporating worker heterogeneity and labour market segmentation into the matching function, the authors show that the degree of heterogeneity varies substantially during recessions. They find that the two worker characteristics that are the most responsible for the break down of the standard matching function are unemployment duration and reason of unemployment. The propensity to form a match decreases as unemployment duration goes up, in addition, those who suffer a permanent job loss, are effected the most.

Sahin et al. (2013) and Sahin et al. (2014) explored the contribution of the mismatch to the rise in unemployment across different levels of disaggregation both in the US and the UK, respectively. They construct a theoretical mismatch index, which measures the fraction of new matches lost because of the misallocation of jobseekers and vacancies. Sahin et al. (2014) find that the job finding rate in 2013 was still half of what it was in 2006. The main results of both the UK and the US research suggest that there is no geographical mismatch in the labour markets, however, occupational mismatch rose steeply during the Great Recession in both countries and remained high in the UK, but declined throughout 2010 in the US.

Smith (2012) adapted the mismatch measuring model of Sahin et al. (2014) to the UK labour market. Using quarterly LFS and Vacancy Survey data, the author estimated the mismatch index and concluded that mismatch contributed to approximately one half on the increase in both steady state and actual unemployment.

As an extension of the work done by Sahin et al. (2014) and Smith (2012) on the UK, this paper contributes to the literature by providing further matching function analysis taking into account worker heterogeneity and labour market segmentation. The emphasis falls on the impact of the Great Recession on the functioning of the labour market and its ability to match unemployed workers to vacant jobs. Furthermore, this paper empirically assesses a number of unemployment and vacancy data sources available in the UK.

I show that the standard matching function over-predicts the job finding rate, which is consistent with the findings of Barnichon and Figura (2015) for the US market, however, the magnitude of mismatch is lower in the UK. Accounting for differences in sub-labour markets, i.e., industries, and worker heterogeneity, reduces the unexplained component of the job finding rate by total of 24%. In line with results from the US, unemployment duration is the most important component of the unemployment pool's composition effect on the job finding rate. Finally, I find that even though changes in the unemployed play an important role in determining the job finding rate, the sharp decline in the job finding rate in the UK after the start of the Great Recession was due to a decreased labour market tightness.

The rest of the paper is organised as follows. Section 2 is an overview of the data. Section 3 describes the methodology applied in this paper and the specification of the matching function. Section 4 summarises the results. Section 5 concludes. More detailed data description and figures are provided in the Appendix.

2 Data

To estimate the aggregate matching function, information about the stock of unemployed workers, the stock of available vacancies and the flow of the matches between the two is needed. In the set up of the extended version of the matching function, unemployed workers are heterogeneous, and so the estimation requires data on workers' demographics, their geographical location, and industry. The period of interest in this paper is 2001-2015, which covers a sufficient time horizon to assess the behaviour of the labour market in the UK before and after the Great Recession of 2008. Data on unemployed workers and their characteristics comes from the longitudinal quarterly Labour Force Survey (LFS). It is a 5 quarter rolling survey, i.e., respondents are followed for 5 quarters, which allows me to also use this data to form a variable of successful matches between vacancies and unemployed workers. Vacancy data is gathered from the Vacancy Survey. Finally, in this section, I will briefly talk about the alternative data sources in the UK.

2.1 LFS unemployment and matches

The definition of unemployment follows the International Labour Organisation (ILO) definition. LFS allows me to calculate the number of unemployed workers for each quarter t, U_t. Furthermore, I can split the unemployed according to various characteristics that can potentially affect their job search behaviour, such as their age, gender, education level, region, ethnicity, unemployment duration, immigration status, and number of dependent children. Data is also disaggregated by industries at 1-digit SIC level. Note that the data

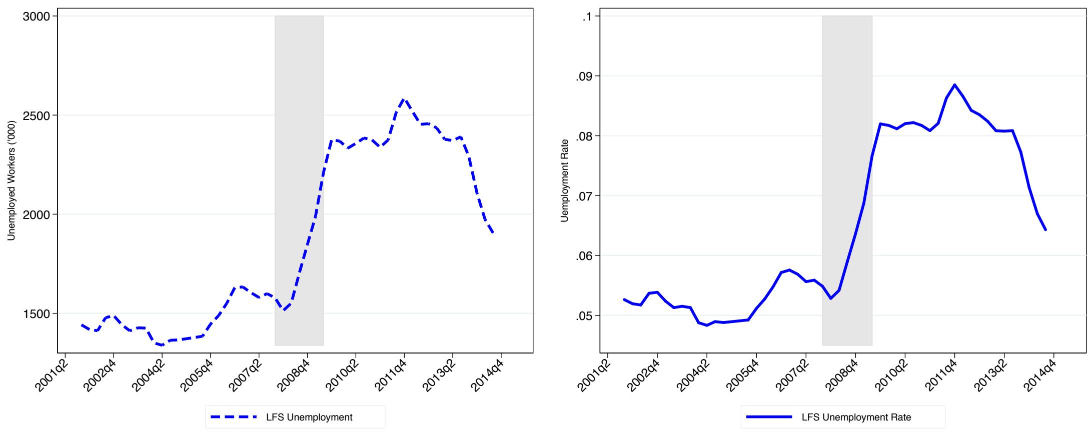

Figure 2: Aggregate Unemployment (LFS, Levels)

Note: Data is smoothed over 2 quarters. Shaded area represents the Great Recession as indicated by FRED (OECD).

is collected on the previous industry of unemployed workers, not the industry they are looking for a job now. In the LFS respondents are followed for five consecutive quarters and asked a number of questions about their employment circumstances. The LFS sample is made up of approximately 40,000 households and 100,000 individuals per quarter. After taking into account all sample restrictions[2], the final sample consists of 59,201 individual observations over the period between 2001Q3 and 2014Q3. For aggregate estimations of the matching function, observations are weighted by population weights provided by the LFS.

Figure 2 plots the unemployment series in both, levels (left panel) and rates (right panel). Unemployment increased dramatically by around 65% during the period of the Great Recession and remained this high for more than three years. Graph suggests that unemployment recovery started in 2013Q2.

Matches

A match between a vacant job and an unemployed worker in this paper is defined as a transition between unemployment state in quarter t and employment state in $t + 1$. As mentioned above, participants of the LFS are followed for five successive quarters and therefore this allows me to calculate the number of matches in each quarter. A job

[2] Limited number of industries surveyed by Vacancy Survey (no Agriculture, Forestry and Fishing sector); I exclude 2005Q1 as the change in employment status coding gives inconsistency in the measure of unemployment. I also need to exclude Energy & Water industry in 2006Q4 as there are too few observations and 2004Q1 as there is no information on education in this period. Missing data is then linearly interpolated

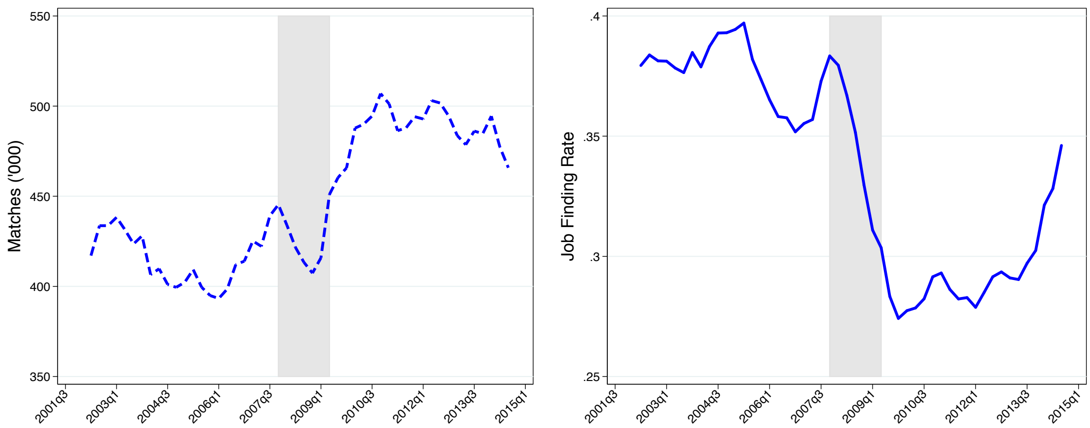

Figure 3: Matches and Job Finding Rate (LFS)

Note: All series are 4-quarter moving averages. Shaded area represents the Great Recession as indicated by FRED (OECD). These series are constructed from reduced population weighted sample.

finding rate then is the ratio between the total number of new matches and the number of unemployed workers.

Figure 3 plots new hires (left) and the job finding rate (right). As the left panel shows, the number of matches started to sharply increase in the mid-recession. This can be explained by the sudden increase in the number of unemployed workers around the same time, thus leading to more matches. However, unemployment increased to a much greater degree than the number of successful matches, which resulted in a sharp decline in the job finding probability. There are some potential measurement issues with the job finding rate that are discussed in the Appendix.

2.2 Vacancies

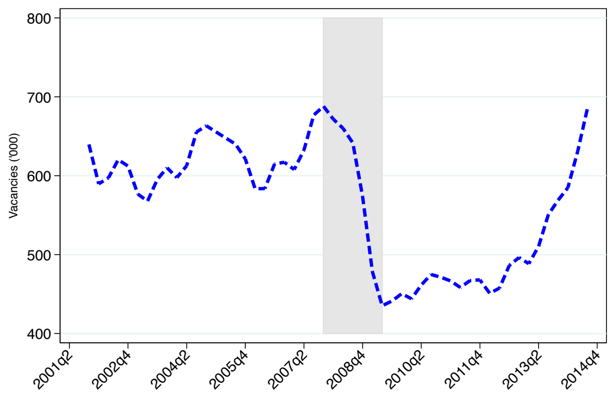

Figure 4: Aggregate Vacancies (Vacancy Survey, Levels)

Note: Vacancy Survey series are deseasonalised and smoothed over 2 quarters. Shaded area represents the Great Recession as indicated by FRED (OECD).

The source of vacancy data in this paper is the Vacancy Survey. It covers all industries except the Agriculture, Forestry and Fishing, which allows us to disaggregate the data into 8 sub-labour markets. The collection of the data by the Vacancy Survey started only in 2001, which will be the starting point of my estimations. The Vacancy Survey interviews 6000 businesses every month, which forms a population of 1.93 million vacancies.

As expected, the Great Recession had a sizeable impact on vacancies in the UK – the number of available jobs decreased by more than 40% (Figure 4). However, conversely to unemployment, vacancies began to gradually recover right after the cessation of the recession. The economic situation has led to a very gradual increase in vacancy creation in the UK with a faster increase in 2012Q2. Vacancy Survey measure of the number of available jobs reached its pre-recessional level in mid-2014, whereas unemployment rate recovered only recently[3].

2.3 Alternative sources of data

The data on unemployment and vacancies is scarce in the UK and matched LFS and Vacancy Survey data covers only a relatively short period of time. Different definitions of unemployment or vacancies may lead to different estimation results. Alternatively, administrative data on vacancies and unemployed workers could be used for the analysis in this paper. However, there is a number of reasons outlined below of why I believe that survey data gives more accurate and credible results.

Unemployed workers

An alternative source of unemployment data is collected by Nomis, which is a service provided by the Office for National Statistics (ONS). Nomis gives administrative data on unemployed workers who are claiming for Jobseeker's Allowance.

LFS unemployment and the claimant counts are consistent to a high degree. Both unemployment series overlap to some extent: claimants are generally recorded as unemployed under ILO definition of unemployment. However, non-claimants can appear among unemployed if they are, for any reason, not eligible for benefits. Analogously, some people recorded in the claimant count would not be counted as unemployed. People can claim Jobseeker's Allowance if they earn low income from part-time work and therefore these people would not be unemployed. LFS unemployment measure is generally higher and more representative of the true population in the UK.

[3]ONS, Regional labour market statistics in the UK: April 2017

Matches

Nomis also provides two plausible measures of total matches between vacancies and unemployed workers. *Claimant off-flows*, the number of people who stop claiming Jobseeker's Allowance, is one of them. However, it is not always true that unemployed workers stop claiming benefits because they found a job. They might do so for other reasons, such as claiming benefits for a maximum period of six months, or a change in other circumstances that make claimants ineligible for JSA. Therefore, claimant off-flows, as a measure of total matches, is subject to measurement error.

Another measure of new hires in the labour market is *vacancy outflow*, which is the count of vacancies that have either been filled by JobCentre Plus or withdrawn by employers. Similarly as with claimant off-flows, we cannot assume that all vacancies were filled by unemployed workers. Some of the jobs might have been taken by people out of the labour force, or workers who experienced job-to-job transitions (without facing unemployment).

Vacancies

Similarly as with unemployment data, vacancy series are also available from two different data sources. In addition to Vacancy Survey, there is also administrative JobCentre Plus (JCP) vacancy statistics, which comes from Nomis.

JCP is the Public Employment Service for Great Britain that accounts for only about one third of the vacancies in the UK. The rest is advertised by employment agencies or directly through employers. JobCentre Plus is a nation-wide employment support service and so it is very plausible that the jobs advertised through this service are targeted at the lower end of the professions scale in terms of skill requirements. JCP vacancy data collection was discontinued in 2012.

Vacancy Survey is more representative of a real vacancy creation situation in the UK. It is not only because of a wider occupational range; in fact, no employer is obligated to notify their vacancies to Job Centres and therefore JCP measure of vacancies is generally below Vacancy Survey. In addition, both small firms and big corporations are surveyed in contrast to only the jobs notified to JobCentre Plus.

Although there are quite a few papers using administrative Nomis data to look at the matching function in the UK (e.g., (Smith, 2012; Pizzinelli and Speigner, 2017; Sahin et al., 2013)), due to reasons stated above, for the analysis in this paper, I focus on survey data rather than administrative. More detailed comparison between the two sources of data is provided in the Appendix.

3 Matching Function

In this section I aim to describe the three matching function specifications estimated in this paper. Starting with the standard aggregate matching function, followed by separate estimations for industry specific matching functions, and finally including the assumption of heterogeneous workers.

3.1 Aggregate matching function

The matching function is assumed to be a concave function increasing in both vacancies and unemployment

$$m_t = f(U_t, V_t),$$

where m_t is the number of new hires in a given quarter t, U_t is the stock of unemployed workers and V_t is the number of available vacancies. New matches are frequently modelled as a Cobb-Douglas matching function, which is usually assumed to exhibit constant returns to scale (CRS) (See Petrongolo and Pissarides (2001))[4]. Assuming the Cobb-Douglas form, the matching function can be written as

$$m_t = \mu_t U_t^{\sigma} V_t^{1-\sigma}, \tag{1}$$

where μ_t is the so called matching efficiency, it affects how quickly matches form for a given number of vacancies and unemployed workers. It consists of a constant term, μ, and an error term, ε_t, which represents random shocks to the labour market, so $\mu_t = \mu e^{\varepsilon_t}$. Empirically, the aggregate matching function can be estimated in the log-linear form

$$\ln f_t = \ln \mu + (1 - \sigma) \ln \theta_t + \varepsilon_t, \tag{2}$$

where θ_t is the labour market tightness equal to $\frac{V_t}{U_t}$, and f_t is the job finding rate, $\frac{m_t}{U_t}$. $\ln \mu_t = \ln \mu + \varepsilon_t$ and therefore $\ln \mu$ is the intercept of the regression and ε_t is the error

[4] In this paper, consistent with the previous findings, the assumption of CRS in the standard aggregate matching function cannot be rejected (Table 1)

term that is assumed to be independent of explanatory variable, θ_t (i.e., strict exogeneity holds: $E(\varepsilon_t|\theta_t) = 0$). σ here is the empirical elasticity with respect to unemployment. In addition to the standard OLS estimation, the matching function is also estimated by CES and FD. To control for seasonality in the regression, a set of monthly or quarterly dummy variables is added, depending on the frequency of the data.

3.2 Industry specific matching function

Some of the unexplained variation in matching efficiency – residual – might be due to industry mismatch between vacancies and unemployed workers. Therefore, I proceed to estimate separate matching functions for each 1-digit SIC industry under two specifications; (1) assuming that the elasticities, σ, are constant across different industries, thus the matching function can be estimated with industry fixed effects, and (2) allowing them to vary, i.e., estimating σ_i. Allowing for variation across industries, the Cobb-Douglas matching function becomes

$$m_{it} = \sum_{i=1}^{I} \mu_i U_{it}^{\sigma} V_{it}^{1-\sigma}, \tag{3}$$

Industry specific matching function aggregates to the standard matching function (Equation 1) with matching efficiency being

$$\mu_t = \sum_{i=1}^{I} \frac{U_{it}}{U_t} \mu_i (\frac{\theta_{it}}{\theta_t})^{1-\sigma}, \tag{4}$$

Parameters of equation (3) then can be estimated with fixed effects using the below log-linear form

$$\ln f_{it} = \ln \mu + (1-\sigma) \ln \theta_{it} + \ln \alpha_i + \varepsilon_{it}, \tag{5}$$

where i is an industry and $i \in \{i, ..., I\}$, $f_{it} = \frac{m_{it}}{U_{it}}$, $\theta_{it} = \frac{V_{it}}{U_{it}}$, and α_i is the unobserved time-invariant industry effect.

To allow for the variation in the elasticities across industries (specification (2)), the aggregate matching function can be estimated industry-by-industry

$$\ln f_{it} = \ln \mu_i + (1 - \sigma_i) \ln \theta_{it} + \varepsilon_{it}, \tag{6}$$

Estimating the matching function equation-by-equation assumes that the error terms are uncorrelated. To remove this assumption, the system of equations is also estimated using Seemingly Unrelated Regressions (SUR).

3.3 A matching function with heterogeneous workers

I further predict that some of the residual from the above estimations can be due to the composition of the unemployment pool. For example, someone with college degree should have higher job finding rate than a school dropout. However, the gap between these two job finding rates can change and fluctuate over time. Barnichon and Figura (2015) developed a method to explicitly incorporate worker heterogeneity into the matching function. In their matching function, unemployed workers are assumed to have different job search efficiencies depending on their type, where in this paper worker type is defined by their age, gender, education level, ethnicity, location, number of dependent children, unemployment duration and immigration status.

Assuming a constant elasticity across segments and including worker search efficiency, the matching function becomes

$$m_{it} = \mu_i V_{it}^{1-\sigma} (s_{it} U_{it})^{\sigma} \tag{7}$$

This matching function aggregates to the standard matching function 1 where the matching efficiency includes both industry and worker heterogeneity effects,

$$\mu_t = \sum_{i=1}^{I} \frac{U_{it}}{U_t} \mu_i s_{it}^{\sigma} \left(\frac{\theta_{it}}{\theta_t}\right)^{1-\sigma}, \tag{8}$$

where s_{it} is worker's search efficiency in sector i over period t and is equal to a weighted average of search efficiencies of specific worker types within this sector, $s_{it} = \sum_{j=1}^{J} \frac{U_{jit}}{U_{it}} s_{jit}$, j denotes worker type ($\in 1, ..., J$). One of the problems that arises while using the LFS data to estimate the aggregate matching function with worker heterogeneity is the inability to disaggregate the data into a time series by many worker types or sub-markets as many cells then contain a zero value.

s_{jit} is assumed to have the following form

$$s_{jit} = e^{\beta X_{jit}} \tag{9}$$

where β is a vector of coefficients for K worker characteristics (given by vector $X_{jit} = [1, x_{jit}^1, ..., x_{jit}^K]$.

By giving an individual job search efficiency the above form (equation 9) and not allowing the parameter vector β to vary over time, it is possible to allocate a search efficiency to every set of worker characteristics.

Given that the matching function takes the form in equation (7), the job finding rate of an individual of type j in industry i over the period t is

$$f_{jit} = \frac{s_{jit}}{s_{it}} \frac{m_{it}}{U_{it}} = \mu_i \frac{s_{jit}}{s_{it}} s_{it}^{\sigma} \theta_{it}^{1-\sigma} \tag{10}$$

and so the job finding probability over period t is

$$F_{jit} = 1 - e^{-\mu_i e^{\beta X_{jit}} \left(\sum_{j=1}^{J} \frac{U_{jit}}{U_{it}} e^{\beta X_{jit}} \right)^{\sigma - 1} \theta_{it}^{1-\sigma}} \tag{11}$$

The micro longitudinal LFS together with the Vacancy Survey provides all the data that is needed to estimate equation (10). Parameters σ, β and μ_i can be estimated by the following log-likelihood function

$$\ell(\beta, \mu_i, \sigma) = \sum_{t=1}^{T} \sum_{i=1}^{I} \sum_{j=1}^{J_i} [(1 - y_{jit}) \ln(1 - F_{jit}) + y_{jit} \ln F_{jit}], \tag{12}$$

where $y_{jit} = 1$ if individual of type j in industry i over a period t finds a job.

4 Results

4.1 The Aggregate Matching Function

Can the evolution of unemployment be explained by the evolution of vacancies? To answer this question, all the estimations are done for the period preceding and including the recession, before 2009Q3, to see how well the model predicts the recovery of the labour market in the UK. Predicted job finding rate is generated and compared with the observed one to measure the residual – mismatch between the number of unemployed workers and available vacancies.

Table 1 presents the elasticities of the aggregate matching function estimated using various specifications. The standard OLS regression gives 0.337 elasticity with respect to vacancies, which is consistent with the previous findings[5]. The test for constant returns to scale does not reject the hypothesis, therefore, for the rest of my estimations I leave the CRS assumption in place.

Even though the Cobb-Douglas specification of the matching function is widely accepted as a good representation of the labour market, it is important to check other functional forms. Although the size of the elasticity of Constant Elasticity of Substitution (CES) estimation (column 2) is consistent with the previous findings in the literature, it is not statistically significant.

Table 1: The Aggregate Matching Function: Elasticities

		OLS[6]	CES	OLS (FE)
$1-\sigma$		0.337**	0.337	0.261**
		(0.053)	(0.357)	(0.050)
	within	–	–	0.4552
R^2	between	–	–	0.2793
	overall	0.8217	0.9957	0.2705
sample size		32	32	8x32

Note: Estimations done for 2001Q3-2009Q3. Robust standard errors in parentheses. CRS test was conducted for OLS estimation with p=0.33. Constant returns to scale hypothesis cannot be rejected. Column 3 gives results of fixed industry effects where regressions are weighted by the average unemployment in each industry. ** significant at the 5 percent level. * significant at the 10 percent level.

[5] Pissarides (1986) has found 0.3 elasticity with respect to vacancies for the UK between 1967 and 1983 using quarterly data.

[6] Due to possible nonstationarity in f_t and θ_t, the aggregate matching function is estimated in first differences (FD) to overcome the spurious correlation problem. Column 2 presents the results. The elasticity with respect to vacancies is not statistically significant from zero in my estimations, suggesting that a quarter may be a significantly long enough period to eliminate this concern.

Borowczyk-Martins et al. (2013) argue that the matching function elasticities suffer from endogeneity bias. They state that random shocks to matching efficiency affect the stock of matches both directly and indirectly through the behaviour of vacancy creation in the labour market. They found that their matching function followed ARMA(3,3) process, however, the data they used is of monthly frequency. To check if the problem exists in my data, I followed their procedure of mechanically finding the right ARMA(p,q) process to eliminate this bias. I do not find any autoregression order that is statistically significant in my data, therefore I conclude that quarterly data does not suffer from endogeneity bias.

4.2 Allowing for variation across segments

It may be that different industries have different matching mechanisms. As mentioned in methodology, there are two ways to incorporate industry effects into the estimations. First, is to assume constant elasticity, therefore to estimate one σ for all industries (Fixed Effects). Second, this assumption can be relaxed and σ_i can be estimated for every industry (equation-by-equation or SUR).

Fixed industry effects estimation results are presented in Table 1, column 3. I find that the elasticity with respect to vacancies is 0.261, which is close to the elasticity from the aggregate estimation, however, shows an upward bias of the standard matching function.

The coefficients from the equation-by-equation estimations are given in Table 2. The significant elasticities from standard OLS estimations vary from 0.154 to 0.500 giving results that closely lay around the elasticity from the aggregate matching function. Some sectors, such as Manufacturing or Distribution, Hotels and Restaurants have higher elasticity with respect to vacancies, suggesting that vacancy creation in these sectors would increase the number of matches by more than an increase in vacancies in, for example, Banking sector, where the elasticity with respect to vacancies is only 0.154. SUR estimation results are presented in column 2 of Table 2. The standard error for each coefficient decreases, however, that does not affect the significance of the estimates. For consistency, i.e., having one elasticity measure, I keep FE estimation for further analysis and comparisons.

Table 2: Industry (1-digit SIC2007) Segmented Matching Function: Elasticities

SIC2007		OLS	SUR
	$1-\sigma$	0.286	0.286
Energy and Water		(0.181)	(0.169)
	R^2	0.0746	
	$1-\sigma$	0.500**	0.500**
Manufacturing		(0.093)	(0.087)
	R^2	0.6391	
	$1-\sigma$	0.289**	0.289**
Construction		(0.085)	(0.080)
	R^2	0.6736	
Distribution,	$1-\sigma$	0.332**	0.332**
Hotels and Restau-		(0.063)	(0.059)
rants	R^2	0.6891	
	$1-\sigma$	0.259**	0.259**
Transport		(0.047)	(0.044)
	R^2	0.5801	
	$1-\sigma$	0.154**	0.154**
Banking		(0.054)	(0.050)
	R^2	0.5536	
Public Adminis-	$1-\sigma$	0.235**	0.235**
tration, Education		(0.119)	(0.111)
and Health	R^2	0.5734	
	$1-\sigma$	-0.138	-0.138
Other Services		(0.117)	(0.0109)
	R^2	0.2281	
	sample size	8x32	8x32

Note: Robust standard errors in parentheses. ** significant at the 5 percent level. * significant at the 10 percent level.

4.3 A matching function with heterogeneous workers

As previously discussed, the matching efficiency may be affected by the changing composition of workers over time. Figure 5 shows that indeed, there were some shifts in certain groups of unemployed workers before and after the start of the Great Recession. After the Great Recession commenced, the pool of unemployed job seekers consisted of more long term, older and better educated unemployed workers than before the recession. Another visible change was at regional level where the share of unemployed in Northern regions increased, while in Southern areas it decreased. This is likely caused by the immobilities of workers as it was especially hard to move from Northern regions to others, such as South East, where there were more jobs available.The differences in housing market in these regions could well add to this result. Houses in the northern regions are up to 3.5 times cheaper than in the South, however, the pay, and especially during the recession, does not compensate for that gap.

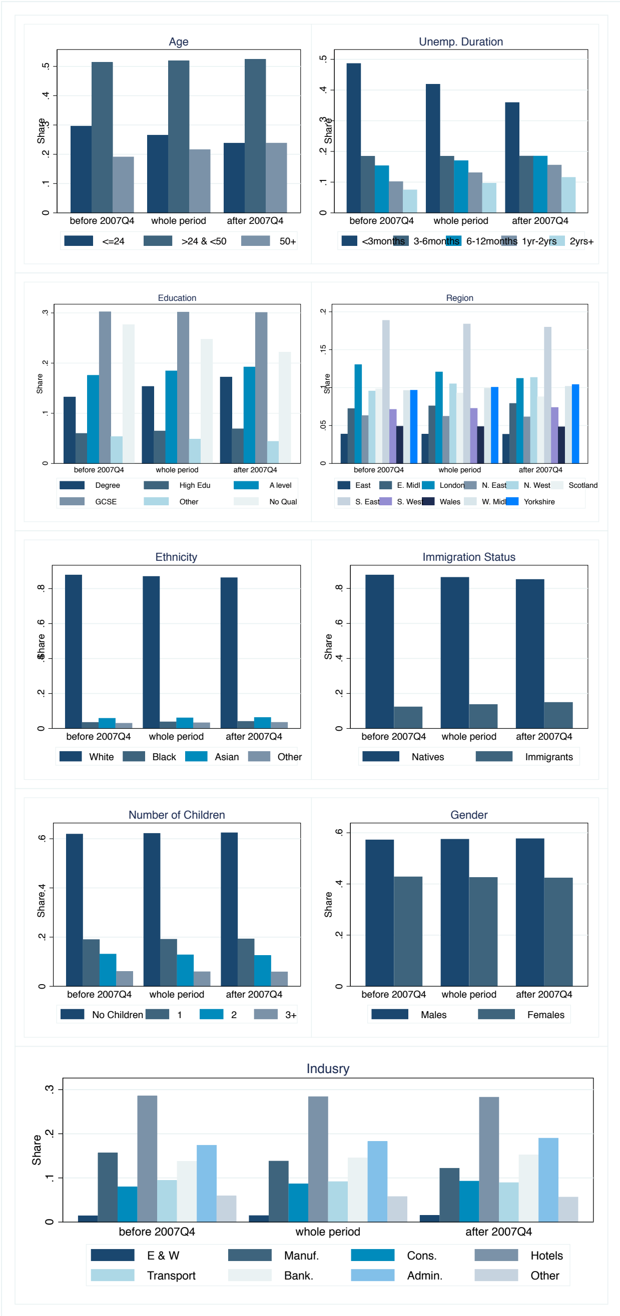

Figure 5: Worker composition: shares over time

Source: The Labour Force Survey (2001Q3 - 2014Q3) and author's calculations.

To estimate the matching function which simultaneously includes labour market segmentation and worker heterogeneity, the individual level LFS data is used. Given that we know if a person found a job or not during a given quarter having a certain set of characteristics (vector X_{jit}) and searching in a sector with a specific labour market tightness (θ_{it}), equation (11) can be estimated by maximising log-likelihood function (12).

Estimation coefficients: job search efficiency

One of the main reasons of estimating the matching function using individual data is to see how efficiently each of the studied group of unemployed workers is searching. Figure 6 gives the estimates of betas – the coefficients on each of worker characteristics that I am using in the aggregate ML estimations.

The results show that age plays a very important role in determining search efficiency. Consistent with Barnichon and Figura (2015) findings for the US, search efficiency is decreasing with age. Unemployed job-seekers that are 24 years old or younger are around 3.5% more likely to find a job than 50 year olds.

Another not less important characteristic is unemployment duration. Individuals that are unemployed less than 3 months are over 10% more likely to find a job than those who are unemployed over 2 years. Unemployment duration between 3 and 6 months shrinks this difference to 6%.

Non-white unemployed workers are less likely to find a job than white ones. People with no qualification have up to 2% lower probability of finding a job than those with a degree.

Unemployed workers in the South have higher job search efficiency than those in North regions or Scotland. Also, higher efficiency is faced by those who have less than three dependent children in their households. It seems that neither immigration status nor gender differences play important roles in determining the search efficiency.

Table 3: The Matching Function (ML): Elasticities

	OLS	ML (1)	ML (2)	ML (3)
$1-\sigma$	0.337**	0.327**	0.298**	0.291**
	(0.053)	(0.020)	(0.033)	(0.034)
Log-likelihood		-23534	-23408	-21578
Sample size	32	35,806	35,806	35,806
Quarter dummies	Yes	Yes	Yes	Yes
Industries	–	–	Yes	Yes
Worker type	–	–	–	Yes

Note: Estimations done for the period preceding and including the Great Recession, before 2009Q3. ** significant at the 5 percent level. * significant at the 10 percent level.

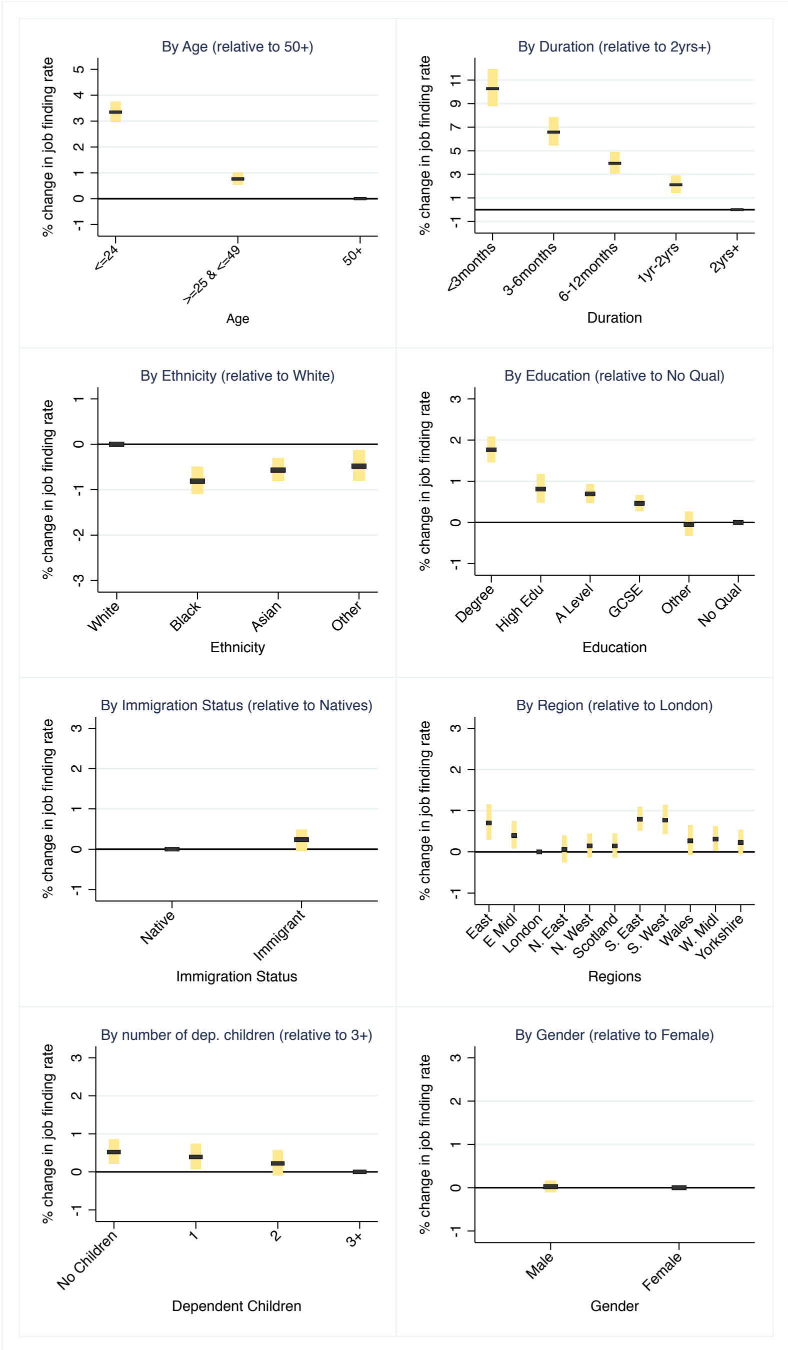

Figure 6: Job Search Efficiency: β

Note: Job search efficiencies from ML estimation controlling for worker composition effect. Estimated on data before 2009Q3.

Elasticities

Table 3 gives the comparison of the estimation coefficients from the OLS regression done on the aggregate matching function with the results from ML regressions. All the elasticities with respect to vacancies from the whole period regressions are very similar and consistent. After adding both labour market segmentation and worker characteristics to the model, the elasticity drops to 0.291 in comparison to the aggregate OLS coefficient – 0.337, which suggests that not controlling for worker heterogeneity and differences in labour market segments biases the estimates upwards. This is consistent with what Barnichon and Figura (2015) find for the US, however, their identified bias is larger.

4.4 Job finding rate and movements in matching efficiency

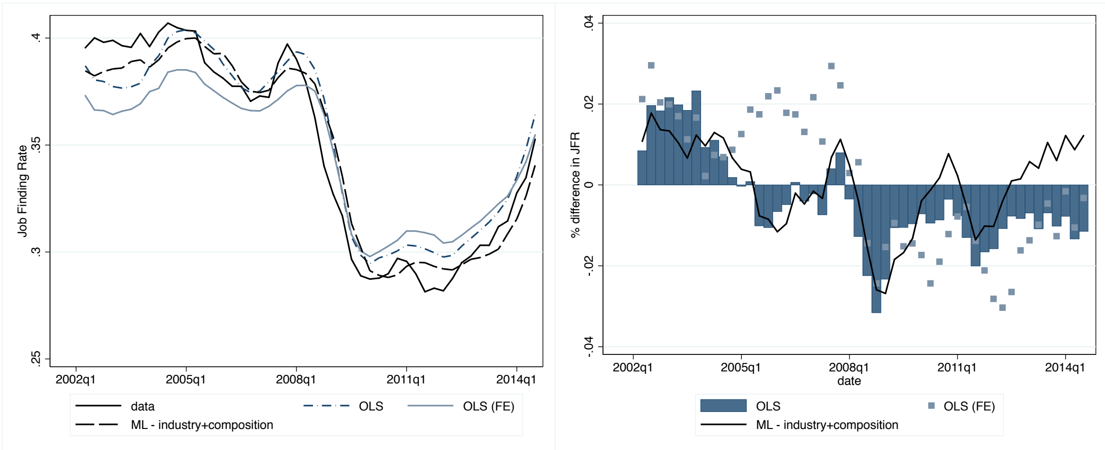

Figure 7: Job Finding Rates: ML estimation

Note: Predicted job finding rates and residuals from ML estimations before 2009Q3.

Figure 7 plots the predicted job finding rates (left) and residuals (right) from 3 estimations: (1) OLS regression; (2) OLS fixed industry effects; (3) ML including industries and worker composition to account for worker heterogeneity in the labour market. Even though standard OLS estimation of the matching function does a pretty good job at predicting the post-recession job finding rate, it seems to constantly over-predict it and so accounting for worker heterogeneity might close the gap and explain some unexplained movements in the matching efficiency. Which is found to be true (Table 4). From the results of augmented Dickey Fuller test, I can conclude that none of the residuals are following random path. However, OLS residuals are consistently negative after the great recession. whereas the residuals from extended ML estimation tend to vary more and are generally smaller. This could be explained by a decrease in GDP growth that the UK economy experienced in the second quarter of 2011[7] when the growth rate dropped below zero first time after the Great Recession and remained low until mid-2012.

[7] http://www.ons.gov.uk/economy/grossdomesticproductgdp/timeseries/ihyn (accessed on 01 May 2016).

Accounting for industry and worker composition effects, shrinks the residuals by 24% in comparison to the residuals from simple OLS estimation for the whole period between 2001Q3 and 2014Q3 (Table 4). However, this seems to be mainly driven by a better performance of the extended matching function before the end of the Great Recession, where Maximum Likelihood estimation (column 3) gives 32% lower residuals than OLS estimation.

Table 4: Residual Sum of Squares

	OLS	OLS (FE)	ML (2)
2001Q3 - 2009Q2	0.0143	0.0248	0.0098
2009Q3 - 2014Q3	0.0057	0.0131	0.0054
2001Q3 - 2014Q3	0.0200	0.0389	0.0153
Quarter dummies	Yes	Yes	Yes
Industries	–	Yes	Yes
Worker type	–	–	Yes

Note: Residual sum of squares from 2001Q3 - 2009Q3 estimations.

4.5 Counterfactuals: isolating the effect of composition vs. labour market tightness

Even though it is now clear that both industry and worker composition effects are important, it is still a question what has driven the matching efficiency to drop to such low level after the beginning of the Great Recession. To segregate the composition effect from the labour market tightness, I isolate these two to see how much of the movement in the job finding rate can be explained by allowing one component to vary and restricting the other at the pre-recessional mean.

Keeping the labour market tightness constant at the pre-recessional level, the estimated job finding rate is

$$\hat{f}_t = \sum_{i=1}^{I} \mu_i s_{it}^{\sigma} \overline{\theta^{1-\sigma}},$$

where $\overline{\theta^{1-\sigma}} = \frac{1}{T_{<2007Q4}} \sum_{t=1}^{T} \sum_{i=1}^{I} \theta_{it}^{1-\sigma}$. This way, the movements coming from the labour market tightness are restricted and the effect on the job finding rate comes only from the changes in job search efficiency, s_{it}.

Letting the labour market tightness move freely and restricting the job search efficiency to its pre-recessional level, the job finding rate becomes

$$\hat{f}_t = \sum_{i=1}^{I} \mu_i \overline{s^{\sigma}} \theta_{it}^{1-\sigma},$$

where $\overline{s^{\sigma}} = \frac{1}{T_{<2007Q4}} \sum_{t=1}^{T} \sum_{i=1}^{I} s_{it}^{\sigma}$.

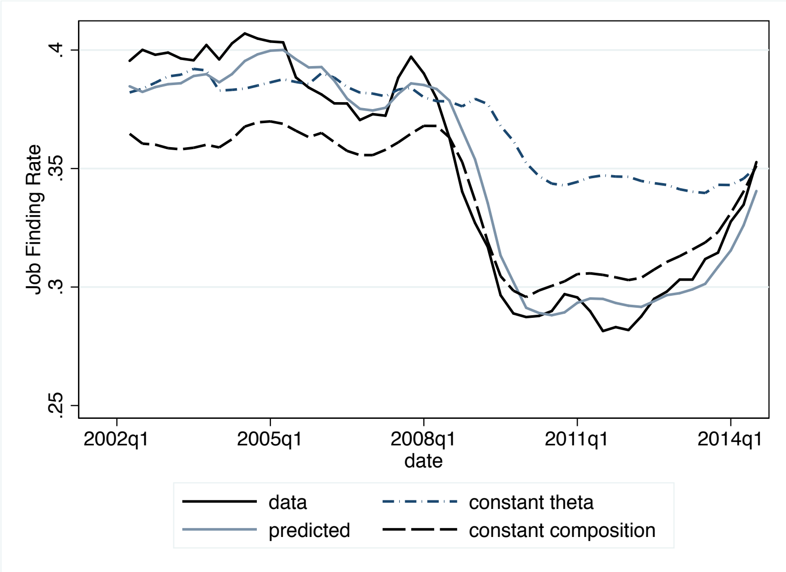

Figure 8: Counterfactual Job Finding Rates

Note: Predicted and counterfactual job finding rates from ML estimation of the matching function accounting for industries and worker heterogeneity. Estimation period - 2001Q3-2009Q3.

The resulting job finding rates are presented in Figure 8. It is easy to see that labour market tightness accounts for the majority of movements in the job finding rate. The effect of worker composition is present, however, it explains just a very small share of a decrease in the job finding rate after the Great Recession. It seems that during the recession, the whole drop in the job finding rate was due to a plummeted labour market tightness and only in the aftermath of the recession the composition of workers became significant. Therefore, the decline in the matching efficiency was mainly due to a large drop in labour demand and an increase in the number of unemployed workers rather than a worsening of the characteristics of the unemployment pool.

4.6 Robustness check: worker composition without unemployment duration

Barnichon and Figura (2015) base their results of composition effect's importance heavily on the duration of unemployment. In line with their results, in my estimations, unemployment duration also accounts for a sizeable part of the composition effect. However, the inclusion of this characteristic into the estimations may lead to an endogeneity bias.

The lower the rate at which people find jobs, the longer the unemployment duration, d_t. Therefore, $f_t = \frac{1}{d_t}$. Trying to explain the movements of the job finding rate by the unemployment duration almost surely will cause imprecision in the estimated coefficients and possible overestimation of the true composition effect.

Figure 9 gives predicted job finding rates and residuals from the ML estimations where a set of worker characteristics excludes unemployment duration. The composition effect almost disappears leading to the conclusion that other characteristics, such as age, gender or education, cannot account for any movements in the job finding rate.

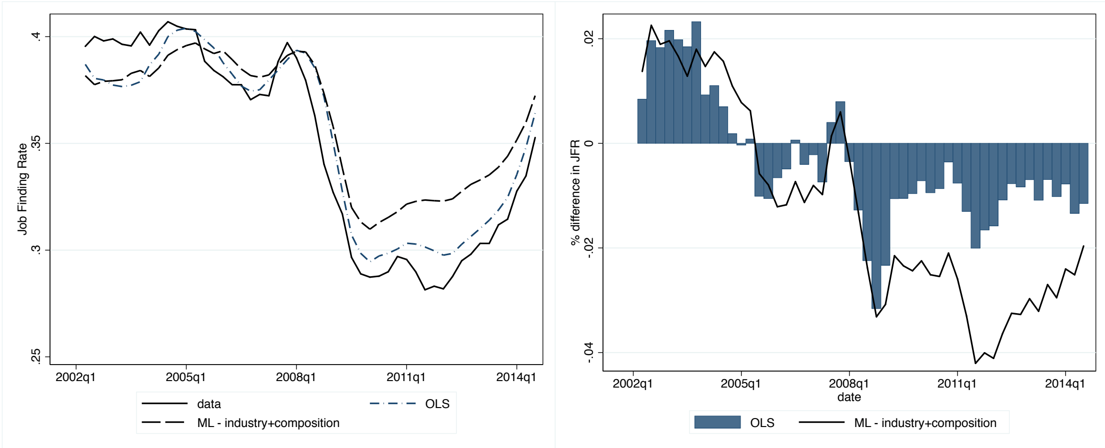

Figure 9: Job Finding Rates: ML estimation without unemployment duration
Note: Predicted job finding rates and residuals from ML estimations on 2001Q3-2014Q3 period.

Figure 10 shows the counterfactual predictions. Keeping labour market tightness constant at its pre-recessional level and allowing the composition effect to move freely results in the failure to account for any of the movements in the job finding rate. This finding once again confirms that the unemployment duration is the most important aspect of the composition of workers in explaining the movements in the job finding rate. However, as discussed above, this may be a result of endogeneity bias.

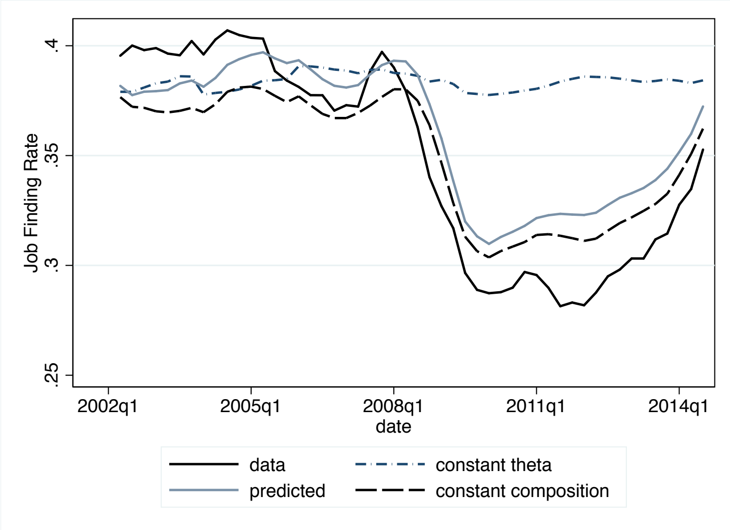

Figure 10: Counterfactual Job Finding Rates without unemployment duration
Note: Predicted and counterfactual job finding rates from ML estimation on 2007Q3 - 2014Q3 period.

5 Conclusion

Recent studies on the matching function in the UK revealed that the matching efficiency between labour market agents decreased during the Great Recession of 2008. Spurred by the lack of investigation into the reasons behind this decline in the efficiency of matching available jobs to unemployed workers, this paper extends the standard aggregate matching function for the UK to explicitly incorporate worker heterogeneity also allowing for a varying matching efficiency across different sub-labour markets – industries.

I show that consistently with the findings for the US (Barnichon and Figura (2015)), job search efficiency declines with age and the length of the unemployment. The results also reveal that accounting for worker composition effect reduces the residuals of the matching function by around 24 percent over the period between 2001Q3 and 2014Q3. Even though this effect seems large, the counterfactuals show that how tight the labour markets are is the most important aspect in explaining the movements in the job finding rate. Therefore, the focus of policy makers should be on the creation of new vacancies rather than targeting specific groups of unemployed workers.

Finally, I discover that in the UK, similarly as in the US, unemployment duration is the only characteristic that significantly contributes to the worker composition effect, leading to a very important question about the possible endogeneity problem, which needs to be tackled in further research on this topic.

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Appendix A Administrative Data Analysis and Comparison

A.1 Data description

A.1.1 Unemployment

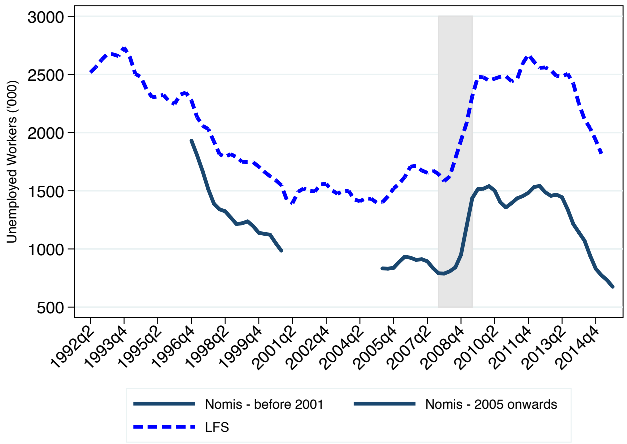


Figure 11: Aggregate Unemployment (Nomis and LFS, Levels)

Note: Nomis Claimant Counts here is a quarterly average of monthly data. Both Nomis and LFS unemployment is smoothed over 2 quarters. Shaded areas represent recessions indicated by FRED (OECD).

Alternative source of unemployment data in the UK is Job Seeker's Allowance Claimant Count (Nomis). LFS unemployment and the claimant counts are consistent to a high degree. However, LFS unemployment measure is generally higher and more representative of the true population in the UK. Figure 11 graphs both unemployment series. Correlation between the two measures is 0.9846 before the break in the data in October 2000 and it is 0.9462 after January 2005. Both unemployment series overlap to some extent: claimants are generally recorded as unemployed in International Labour Organization (ILO) definition of unemployment (see Table 5 for details). However, non-claimants can appear among unemployed if they are not eligible for benefits for one of the below reasons[8]:

- They are only looking for part-time work;
- They are under 18 and are looking for work but do not take up the offer of a Youth Training place;
- They are students looking for vacation work;

[8] https://www.detini.gov.uk/sites/default/files/publications/deti/Summary%20LFS%20CC%20explanation%20for%20the%20web.pdf (accessed on 9 January 2016)

- They have left their job voluntarily.

Analogously, some people recorded in the claimant count would not be counted as unemployed. People can claim Jobseeker's Allowance if they earn low income from part-time work and therefore these people would not be unemployed. Table 5 summarises the main features of the two data sources.

Table 5: Specification of Unemployment Data in the UK

	JSA Claimant Count	**LFS**
Type	Administrative	Household Survey
Definition of unemployment	Jobseekers that are out of work, capable of, available for and actively seeking work during the week in which their claim is made	ILO - Answer 'yes' to both 'whether the respondent is available to work in the next 2 weeks' and 'whether he/she has looked for work in the last 4 weeks'
Period	From July 1996 and regularly updated. Break between October 2000 and January 2005. Quarterly before October 2000, monthly from January 2005	Quarterly from 1992 and updated regularly
Sample	All JSA claimants	50000 households every quarter
Worker characteristics	age gender claim duration	age gender unemployment duration marital status ethnicity qualifications
Labour market characteristics	region (UK excl. NI) occupation (1-digit SOC2000)	region (UK excl. NI) occupation (1-digit SOC1990) industry (1-digit SIC2007)
Collection period	Second Thursday of a given month	Respondents are interviewed over 13 weeks in a given quarter and are asked about their situation and activities in a reference week (a seven day period that ends on a Sunday). Most of the interviews are carried out in the week following the reference week

Alternative measures of unemployment

The International Labour Organization (ILO) definition of unemployment is limited in some sense because it ignores those who are out of the labour force. The alternative measures suggested by the Bureau of Labor Statistics (BLS) allows to deepen the understanding of true unemployment situation in the UK. In this paper, all six unemployment rates are produced using the LFS data. U1-U2 give narrower definition of unemployment, U3 is the official ILO definition, while U4-U6 give broader concept of unemployment[9]. U1 gives the number of long-term (15 weeks or longer) unemployed workers as a percent of the labour force. The closest alternative in the LFS is unemployment of 3 months or longer. The broader definitions, U4-U6, include discouraged or marginally attached workers. Discouraged workers fall as a part of marginally attached. Discouraged are those workers who are not in the labour force, they would like to and are able to work, they have looked for work in the past 12 months, but not in the past 4 weeks, because they believe that there are no jobs available for them. Marginally attached are all those able and willing to work that were not looking for work in the past 4 weeks for any reason. All broader measures represent potential groups of workers who under certain conditions would work and therefore in some ways they can be considered as unemployed.

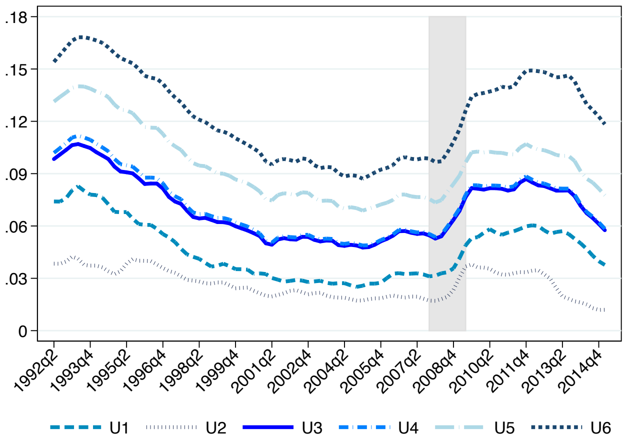


Figure 12: Alternative Measures of Unemployment

Note: All measures are constructed using LFS. 2-quarter moving averages. These measures were constructed using Bureau of Labor Statistics definitions. Shaded area represents the Great Recession as indicated by FRED (OECD).

Figure 12 plots U1-U6 unemployment rates. All six alternative measures generally move together. There was a sharp increase in all unemployment rates during the Great Recession. U6 - the broadest unemployment measure, which also includes part-time workers who are not working full-time for economic reasons - surged from around 10% in the beginning of the recession to as high as 15% in the aftermath of the recession.

[9]Details and definitions of BLS alternative measures of unemployment can be found here: http://www.bls.gov/lau/stalt.htm (accessed on 9 January 2016).

A.1.2 Matches

Nomis - Claimant Off-flows and Vacancy Outflows

Nomis provides two plausible measures of total matches. *Claimant off-flows*, the number of people who stop claiming Jobseeker's Allowance, is one of them. However, it is not always true that unemployed workers stop claiming benefits because they found a job. They might do so for other reasons, such as claiming benefits for a maximum period of six months, or a change in other circumstances that make claimants ineligible for JSA. Therefore, claimant off-flows, as a measure of total matches, is subject to measurement error.

Another measure of new hires in the labour market is *vacancy outflow*, which is the count of vacancies that have either been filled by JobCentre Plus or withdrawn by employers. Similarly as with claimant off-flows, we cannot assume that all vacancies were filled by unemployed workers. Some of the jobs might have been taken by people out of the labour force, or workers who experienced job-to-job transitions (without facing unemployment).

It is not possible to correct for these measurement errors, however, as suggested by Sahin et al.(2013) in their working paper, one might want to take the average of the two possible measures for the estimation of the matching function.

Data specifications, that apply to JSA claimant count and JCP vacancies (i.e., type, period, collection period, worker and labour market characteristics given in Tables 5 and 6) are also true for claimant off-flows and vacancy outflows.

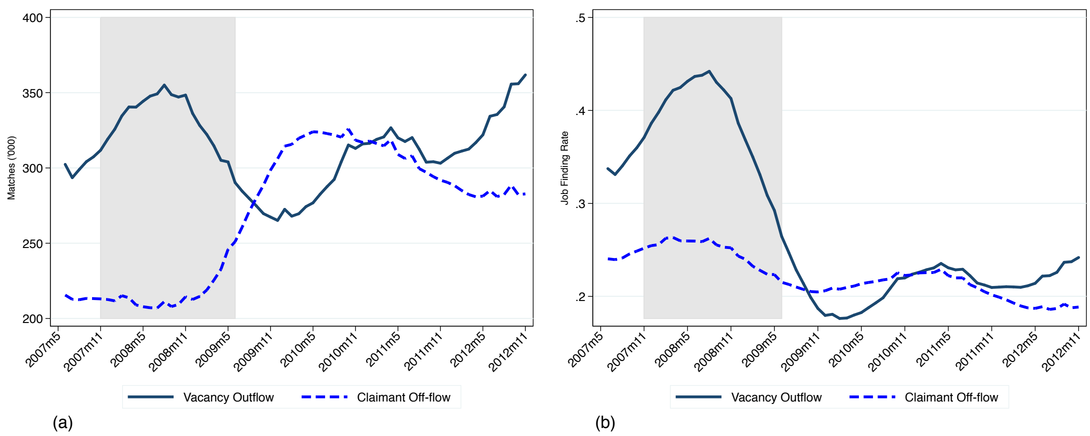


Figure 13: Matches and Job Finding Rate (Nomis)
Note: All series are 12-month moving averages. Shaded areas represent recessions indicated by FRED (OECD).

Figure 13 plots new hires (a) and job finding rate (b) using both claimant off-flows and vacancy outflows. Interestingly, the correlation between the two new matches series is -0.4520. Midway through the Great Recession, the number of people who stopped claiming JSA benefits started to increase. With a sharp increase in the number of claimants, the count of people who run out of benefits (claim for the maximum period) is also going up. This may explain an increase in the number of matches given by claimant off-flows.

Panel (b) in Figure 13 shows the monthly job finding rates constructed using claimant off-flows and vacancy outflows. Both rates generally move together, the correlation between the two is 0.8715. Before and during the Great Recession, however, vacancy outflows give much higher job finding probability. Both series show a decline in the job finding rate during the recession.

A.2 Alternative LFS measure of the job finding rate

In addition to UE transitions as a measure of the number of matches between vacant jobs and unemployed workers, I construct an alternative measure. If a person is employed for 3 or less months, I count this as a new match. However, I need to account for job-to-job transitions. I observe people who had jobs in the previous quarter and who again are employed in the current quarter. If they left a paid job in the last 3 months, this is counted as a job-to-job transition. This measure, however, does not account for inactivity to employment transitions as it is not possible to tell where the newly employed people are coming from and if they were unemployed last term. Therefore, I argue that UE transitions is a better measure of the new matches in the labour market.

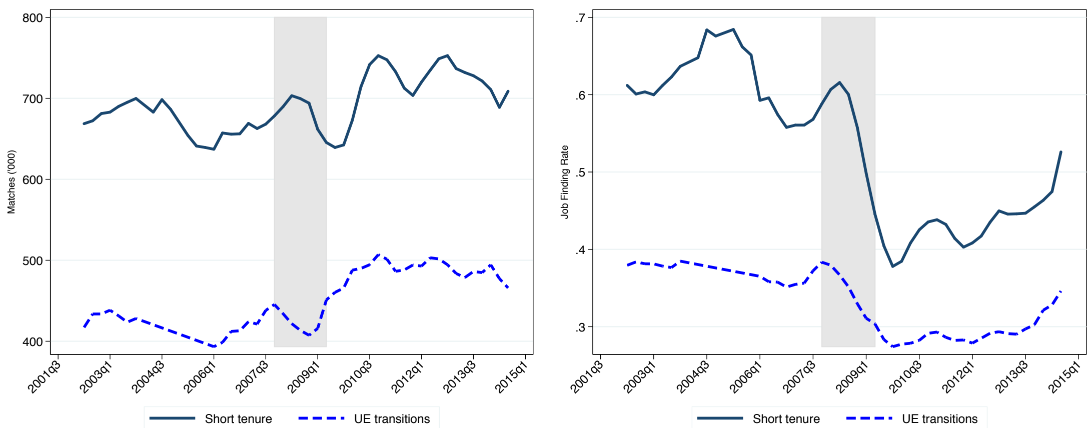


Figure 14: Matches and Job Finding Rate (LFS)

Note: All series are 4-quarter moving averages. Shaded area represents the Great Recession as indicated by FRED (OECD).

Figure 14 plots both LFS matches series (left) and job finding rates (right).

The UE transitions measure of new hires is generally below the short tenure measure of matches. Over the whole period, the correlation between the two series is 0.7065. The number of new hires constructed from the short tenure matches being consistently above the UE transitions measure can be explained as follows. In the UE case, if a person is recorded as employed last quarter and is again employed this quarter, there is no new job finding recorded. However, during the 3-month period, the same person might have experienced a short unemployment spell, and in the short tenure data analysis, this would be captured and counted as a new match.

The graph on the right side of Figure 14 shows job finding rates using both LFS measures of matches. Both series move together and record a sharp decrease in the probability of finding a new job during and after the Great Recession. The correlation coefficient between the two rates is 0.9794.

A.2.1 Vacancies

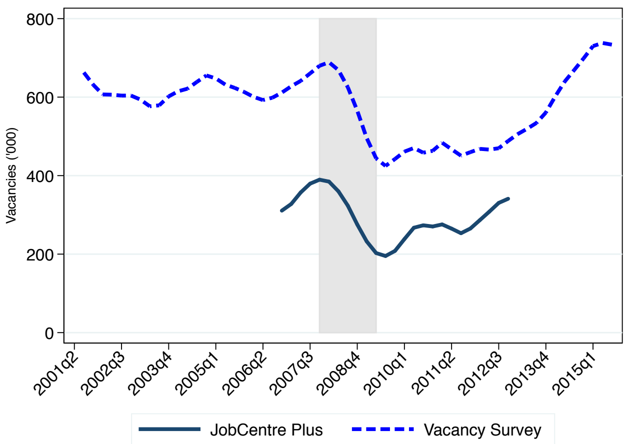


Figure 15: Aggregate Vacancies (Nomis and Vacancy Survey, Levels)

Note: Nomis JobCentre Plus vacancies and Vacancy Survey here are quarterly averages of monthly data. Both Nomis and Vacancy Survey series are deseasonalised and smoothed over 2 quarters. Shaded areas represent recessions indicated by FRED (OECD).

Similarly as with unemployment data, vacancy series are also available from two different data sources. In addition to Vacancy Survey, there is also Administrative JobCentre Plus (JCP) vacancy statistics, which come from Nomis. Table 6 provides a summary of vacancy data specifics in the UK.

JCP is the Public Employment Service for Great Britain that accounts for only about one third of the vacancies in the UK. The rest is advertised by employment agencies or

Table 6: Specification of Vacancy Data in the UK

	JobCentre Plus	Vacancy Survey
Type	Administrative - supplied by Department for Work and Pensions (DWP)	Business Survey
Period	From April 1994 until November 2012. Break between October 2000 and April 2004. Quarterly before October 2000, monthly from April 2004	Monthly from April 2001 and updated regularly
Sample	All vacancies notified to Job Centres	6000 businesses every month, population of 1.93 million
Labour market characteristics	region (UK excl. NI) occupation (1-digit SOC2000) industry (1-digit SIC2003)	industry (1-digit SIC2007, excl. Agriculture, Forestry and Fishing) business size
Collection period	First Friday of a given month	Data is collected over 16 working days starting the first Friday of the month, unless it is the first day of the month, then the reference day is moved to the second Friday of the month

directly through employers. JobCentre Plus is a nation-wide employment support service and so it is very plausible that the jobs advertised through this service are targeted at the lower end of the professions scale in terms of skill requirements. Similarly as with claimant count data, JCP vacancies were also discontinued for a period of time, however, due to the measurement differences, the data before and after the break are not compatible. In addition, the procedures for recording and handling vacancies were changed in May 2006. From this point in time, a date of vacancy closure is agreed with the employer at the time of vacancy notification and therefore jobs are automatically withdrawn unless the employer advises that a later closure date is required. Over time, this would reduce the number of unfilled vacancies. To avoid measurement error coming from these changes, the analysis of JCP data starts in July 2006.

Vacancy Survey is more representative of a real vacancy creation situation in the UK. It is not only because of a broader occupational range; in fact, no employer is obligated to notify their vacancies to Job Centres and therefore JCP measure of vacancies is generally below Vacancy Survey. Figure 15 shows plots of the two vacancy series. After the change in JPC vacancy handling, the correlation between the two measures is 0.8284.

A.3 Alternative data analysis

Figure 16 shows the plots of the predicted job finding rates using the administrative Nomis data. The results presented in (a) and (c) graphs are from the matching function estimation using claimant off-flows as a measure of total matches. The standard aggregate matching function estimated over the whole period (July 2006 - November 2011) explains the movements of the job finding rate very well before and during the Great Recession. However, it underestimates the job finding probability in the aftermath of the recession until the next recession in the end of 2011, when the result is the opposite and the matching function over-predicts the job finding rate. This also holds for the estimation of the matching function before the peak of the Great Recession - the collapse of Lehman Brothers in September 2008 (c).

The bottom two graphs ((b) and (d)) repeat the estimation of the matching function using vacancy outflows as a measure of matches. In this case, the predicted job finding rate turns out to be very close to the actual data. However, the matching function estimated prior to September 2008 under-predicts the job finding probability after the Great Recession.

Table 7 provides the estimated coefficients of the aggregate matching function. The elasticities from the estimations using claimant off-flows and vacancy outflows as measures of total matches are very different. Claimant off-flows give a more consistent estimate of the elasticity with respect to vacancies to the one found by Pissarides (1986). It is 0.214 for the whole period estimation compared to 0.3. When vacancy outflows are used as a measure of total matches, the estimated elasticity is 0.709 (regression (2) in Table 7).

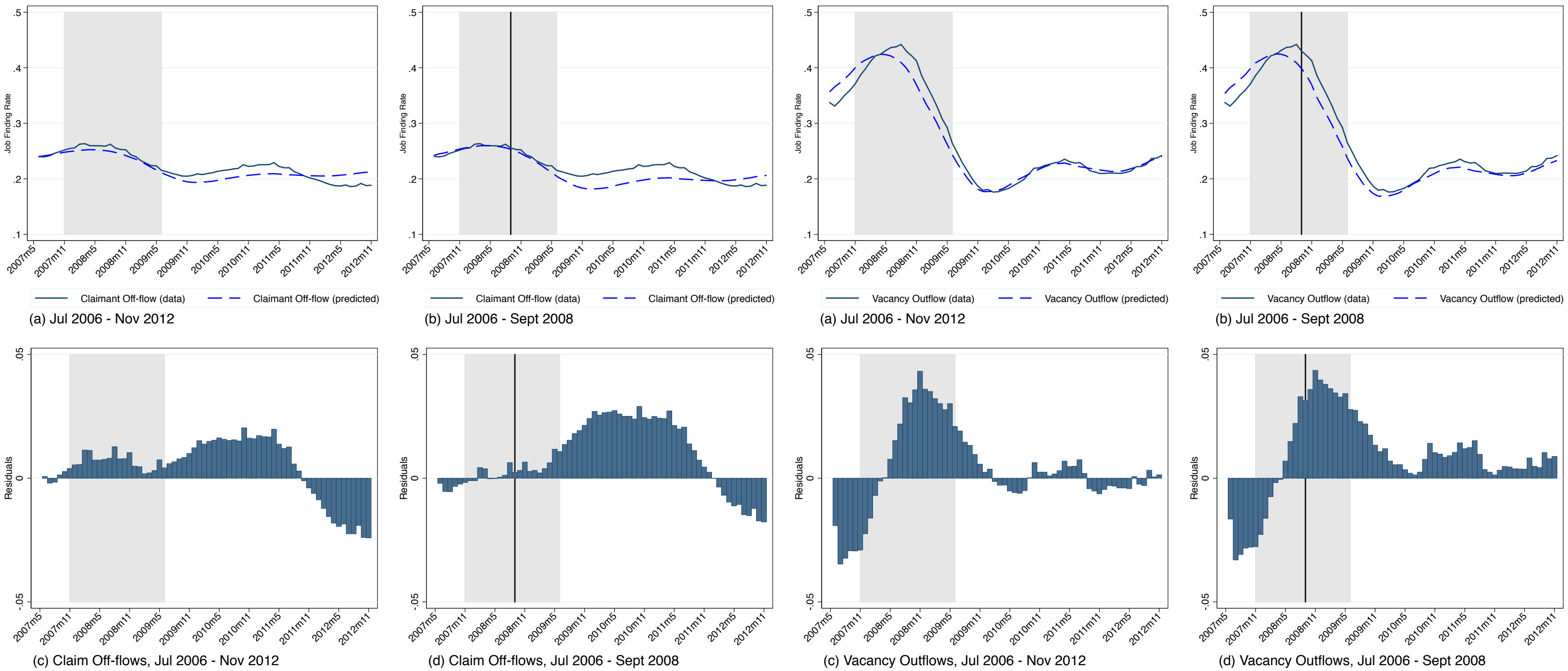
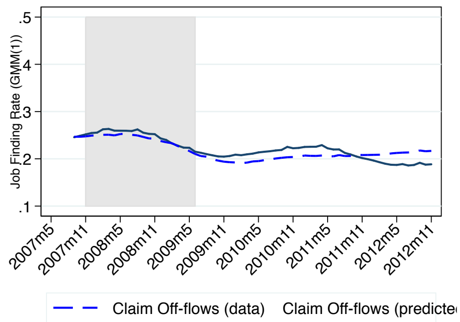
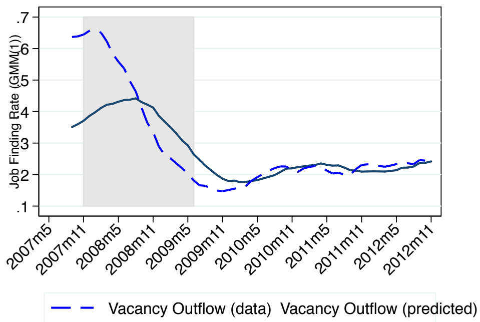


Figure 16: Job Finding Rate: The Aggregate Matching Function (Nomis-OLS)

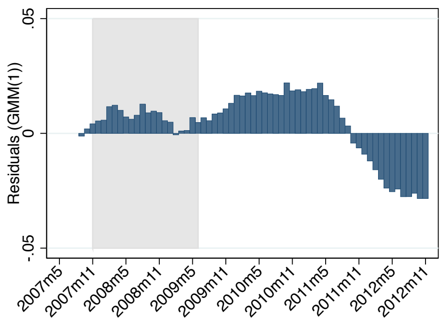
Note: The aggregate matching function estimated on the whole period and before the bankruptcy of Lehman Brothers. All series are 12-month moving averages. Shaded areas represent 2008-2009 recession as indicated by FRED (OECD).



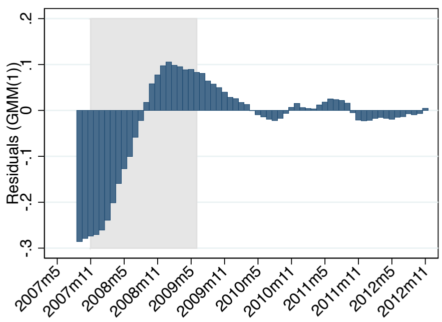
(a) Jul 2006 - Nov 2012



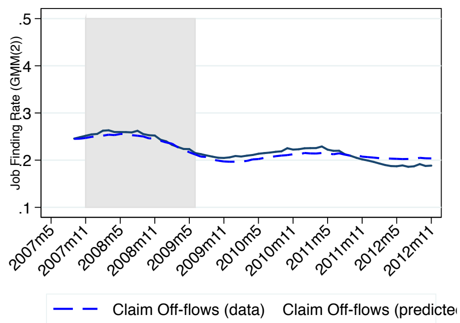
(a) Jul 2006 - Nov 2012



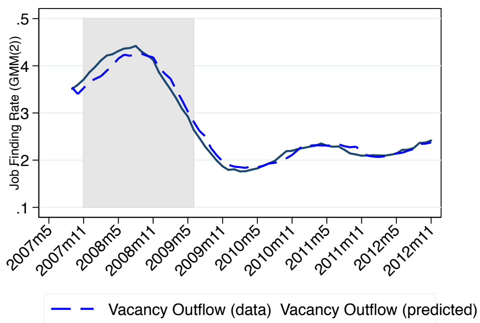
(b) Claim Off-flows, Jul 2006 - Nov 2012



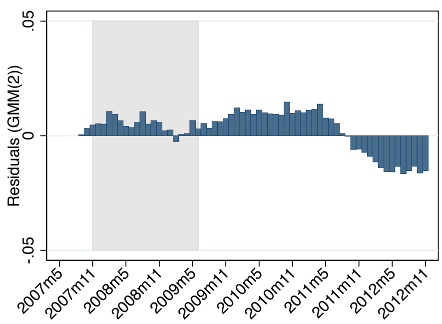
(b) Vacancy Outflow, Jul 2006 - Nov 2012



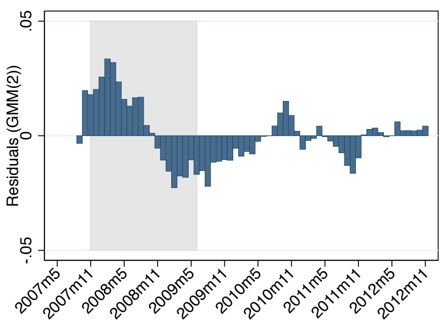
(c) Jul 2006 - Nov 2012



(c) Jul 2006 - Nov 2012



(d) Claim Off-flows, Jul 2006 - Nov 2012



(d) Vacancy Outflow, Jul 2006 - Nov 2012

Figure 17: Job Finding Rate: The Aggregate Matching Function (Nomis-GMM)

Note: The aggregate matching function estimated by GMM (Borowczyk-Martins et al. (2013)) on the whole period and before the bankruptcy of Lehman Brothers. All series are 12-month moving averages. Shaded areas represent 2008-2009 recession as indicated by FRED (OECD).

Table 7: The Aggregate Matching Function: Elasticities

		Nomis		Longitudinal LFS	
		(1) Claim Off-fows	(2) Vacancy Outflows	(1) Short tenure	(2) UE transitions
OLS	$1-\sigma$	0.214**	0.709**	0.574**	0.337**
		(0.032)	(0.038)	(0.032)	(0.053)
	R^2	0.5201	0.8766	0.8941	0.8217
	test for CRS	p=0.03	p=0.21	p=0.10	p=0.33
	sample size	77	77	53	32
FD	$1-\sigma$	0.733**	0.986**	0.740**	0.140
		(0.279)	(0.285)	(0.200)	(0.053)
	R^2	0.3802	0.3514	0.8265	0.8665
	sample size	76	76	52	31
CES	$1-\sigma$	0.679	0.678**	0.815**	0.337
		(0.432)	(0.220)	(0.137)	(0.357)
	R^2	0.9861	0.9839	0.9962	0.9957
	sample size	77	77	53	32
GMM (1)	ARMA	(3,3)	(3,4)	(1,1)	–
	$1-\sigma$	0.213**	0.759**	0.593**	–
		(0.030)	(0.046)	(0.059)	–
	sample size	73	72	51	–
GMM (2)	ARMA	(3,3)	(3,4)	(1,1)	–
	$1-\sigma$	0.213**	0.688**	0.588**	–
		(0.051)	(0.218)	(0.035)	–
	Sargan test	1: 0.181: 0.671	1: 0.793: 0.373	1: 0.026: 0.872	–
	sample size	73	72	51	–
	frequency	monthly	monthly	quarterly	quarterly

Note: Standard errors in parentheses (robust for OLS and CES regressions). **Regression 1** uses Nomis unemployment and vacancy data, and claimant off-flows as a measure of matches. **Regression 2** uses Nomis unemployment and vacancy data, and vacancy outflows as a measure of matches. **Regression 3** uses LFS and VS data, and panel short tenure matches. **Regression 4** uses LFS and VS data, and panel UE transitions as matches. GMM (1) - just identified. GMM(2) - overidentified.
** significant at the 5 percent level. * significant at the 10 percent level.

Table 8: Occupation (1-digit SOC2000) Segmented Matching Function: Elasticities (Nomis)

SIC2007	Specification		(1) Claim Off-fows	(2) Vacancy Outflows
	whole period estimation			
1-Managers and Senior Officials	OLS	$1-\sigma$	0.159**	0.742**
			(0.029)	(0.042)
		R^2	0.5551	0.8635
	OLS (FD)	$1-\sigma$	0.063	0.500
			(0.230)	(0.296)
		R^2	0.2846	0.2340
2-Professional Occupations	OLS	$1-\sigma$	0.152**	0.741**
			(0.037)	(0.047)
		R^2	0.5660	0.8293
	OLS (FD)	$1-\sigma$	0.094	0.210
			(0.208)	(0.294)
		R^2	0.3559	0.3323
3-Associate Professional and Technical Occupations	OLS	$1-\sigma$	0.206**	0.687**
			(0.049)	(0.072)
		R^2	0.4982	0.6818
	OLS (FD)	$1-\sigma$	0.409**	0.476
			(0.197)	(0.265)
		R^2	0.3393	0.2697
4-Administrative and Secretarial Occupations	OLS	$1-\sigma$	0.166**	0.779**
			(0.022)	(0.040)
		R^2	0.6283	0.8409
	OLS (FD)	$1-\sigma$	0.217	0.051
			(0.119)	(0.164)
		R^2	0.3648	0.1867
5-Skilled Trades Occupations	OLS	$1-\sigma$	0.096**	0.743**
			(0.022)	(0.028)
		R^2	0.5808	0.9321
	OLS (FD)	$1-\sigma$	0.298	0.511*
			(0.226)	(0.262)
		R^2	0.4105	0.4286
6-Personal Service Occupations	OLS	$1-\sigma$	0.317**	0.694**
			(0.044)	(0.047)
		R^2	0.5330	0.7018
	OLS (FD)	$1-\sigma$	0.748**	0.890**
			(0.321)	(0.377)
		R^2	0.3658	0.2677
7-Sales and Customer Service occupations	OLS	$1-\sigma$	0.212**	0.743**
			(0.022)	(0.036)
		R^2	0.7116	0.8643
	OLS (FD)	$1-\sigma$	0.173	-0.018
			(0.168)	(0.169)
		R^2	0.3316	0.2970
8-Process, Plant and Machine Operatives	OLS	$1-\sigma$	0.115**	0.725**
			(0.025)	(0.032)
		R^2	0.5159	0.9116
	OLS (FD)	$1-\sigma$	0.168	0.476**
			(0.185)	(0.221)
		R^2	0.3997	0.3983
9-Elementary Occupations	OLS	$1-\sigma$	0.223**	0.616**
			(0.031)	(0.037)
		R^2	0.5629	0.8591
	OLS (FD)	$1-\sigma$	0.503**	0.632**
			(0.235)	(0.282)
		R^2	0.3545	0.3429
		sample size	77 (FD-76)	77 (FD-76)

Note: Robust standard errors in parentheses. **Regression 1** uses Nomis unemployment and vacancy data, and claimant off-flows as a measure of matches. **Regression 2** uses Nomis unemployment and vacancy data, and vacancy outflows as a measure of matches. ** significant at the 5 percent level. * significant at the 10 percent level.

Table 9: OLS Fixed Effects

		Nomis		Longitudinal LFS	
		(1) Claim Off-fows	(2) Vacancy Outflows	(3) Short tenure	(4) UE transitions
whole period estimation					
Occupation	$1-\sigma$	0.173**	0.708**	-	-
		(0.021)	(0.028)	-	-
	R^2				
	within	0.5362	0.8395	-	-
	between	0.0219	0.9498	-	-
	overall	0.3161	0.8692	-	-
	sample size	9x77	9x77	-	-
Industry	$1-\sigma$	-	-	0.537**	0.317**
		-	-	(0.035)	(0.031)
	R^2				
	within	-	-	0.6489	0.5093
	between	-	-	0.3258	0.2960
	overall	-	-	0.3899	0.3157
	sample size	-	-	8x53	8x53
before the bankruptcy of Lehman Brothers					
Occupation	$1-\sigma$	0.165**	0.635**	-	-
		(0.036)	(0.094)	-	-
	R^2				
	within	0.7613	0.6011	-	-
	between	0.0244	0.8519	-	-
	overall	0.5554	0.6987	-	-
	sample size	9x26	9x26	-	-
Industry	$1-\sigma$	-	-	0.559**	0.063
		-	-	(0.179)	(0.089)
	R^2				
	within	-	-	0.5111	0.3215
	between	-	-	0.2368	0.2658
	overall	-	-	0.2235	0.1652
	sample size	-	-	8x25	8x25

Note: Robust standard errors in parentheses. **Regression 1** uses Nomis unemployment and vacancy data, and claimant off-flows as a measure of matches. **Regression 2** uses Nomis unemployment and vacancy data, and vacancy outflows as a measure of matches. **Regression 3** uses LFS and VS data, and panel short tenure matches. **Regression 4** uses LFS and VS data, and panel UE transitions as matches. All regressions are weighted by the average unemployment in each industry. ** significant at the 5 percent level. * significant at the 10 percent level.

Table 10: Worker composition: by industry

			Industry							
		Whole Sample	Energy & Water	Manufacturing	Construction	Hotels	Transport	Banking	Admin.	Other
No. of obs.		59,201	860	8,171	5,121	16,812	5,417	8,601	10,800	3,419
Age	<25	0.265	0.216	0.191	0.231	0.410	0.194	0.210	0.173	0.335
	>=25 & <50	0.519	0.500	0.519	0.524	0.451	0.548	0.572	0.579	0.487
	50+	0.216	0.284	0.290	0.245	0.139	0.258	0.219	0.248	0.178
U. dur.	< 6 months	0.603	0.621	0.544	0.538	0.616	0.575	0.635	0.640	0.625
	> 6 months	0.397	0.379	0.456	0.462	0.384	0.425	0.365	0.360	0.375
Ethnicity	White	0.870	0.917	0.888	0.933	0.853	0.858	0.852	0.861	0.889
	Black	0.038	0.027	0.027	0.023	0.032	0.045	0.049	0.049	0.039
	Asian	0.060	0.037	0.061	0.026	0.077	0.071	0.061	0.053	0.040
	Other	0.033	0.017	0.025	0.019	0.037	0.027	0.038	0.037	0.032
Education	Degree	0.153	0.156	0.094	0.053	0.074	0.163	0.250	0.280	0.178
	High Edu.	0.065	0.084	0.060	0.037	0.046	0.064	0.730	0.102	0.068
	A Level	0.184	0.187	0.161	0.197	0.199	0.168	0.188	0.177	0.187
	GCSE	0.302	0.283	0.296	0.357	0.349	0.290	0.260	0.243	0.311
	Other	0.048	0.034	0.060	0.055	0.058	0.047	0.036	0.037	0.040
	No Qual.	0.247	0.257	0.329	0.301	0.274	0.268	0.193	0.161	0.216
Imm. status	Native	0.863	0.903	0.869	0.921	0.862	0.858	0.838	0.851	0.874
	Immigrant	0.137	0.097	0.131	0.079	0.138	0.142	0.162	0.149	0.126
Region	North	0.268	0.288	0.305	0.292	0.268	0.252	0.233	0.268	0.249
	Midlands	0.175	0.179	0.234	0.154	0.176	0.184	0.146	0.168	0.141
	South	0.416	0.315	0.315	0.381	0.417	0.437	0.489	0.428	0.466
	Wales	0.047	0.056	0.061	0.059	0.045	0.040	0.040	0.051	0.047
	Scotland	0.093	0.162	0.084	0.114	0.094	0.087	0.092	0.084	0.097
Dep. child.	No Child.	0.622	0.713	0.675	0.673	0.585	0.658	0.641	0.575	0.619
	1	0.191	0.158	0.160	0.159	0.222	0.0154	0.180	0.206	0.214
	2	0.128	0.084	0.109	0.110	0.131	0.127	0.122	0.158	0.117
	3+	0.059	0.045	0.056	0.057	0.063	0.061	0.057	0.061	0.050
Gender	Male	0.575	0.813	0.771	0.923	0.497	0.755	0.547	0.315	0.514
	Female	0.425	0.187	0.229	0.077	0.503	0.245	0.453	0.685	0.486
Whole sample			0.015	0.138	0.087	0.284	0.092	0.145	0.182	0.058

Note: Sample period 2001 Q3 – 2014 Q3.