Mismatch Unemployment in the U.K. †

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Abstract

This paper analyzes mismatch unemployment in the U.K. labor market. We find no evidence of a worsening in geographical mismatch. At the 3-digit occupational level, instead, mismatch rose sharply during the recession, and remained high. This persistent increase in occupational mismatch explains between 1/4 and 1/3 of the total rise of the unemployment rate in the U.K. since 2007.

[†] The opinions expressed herein are those of the authors and not necessarily those of the Federal Reserve Bank of New York or the Federal Reserve System.

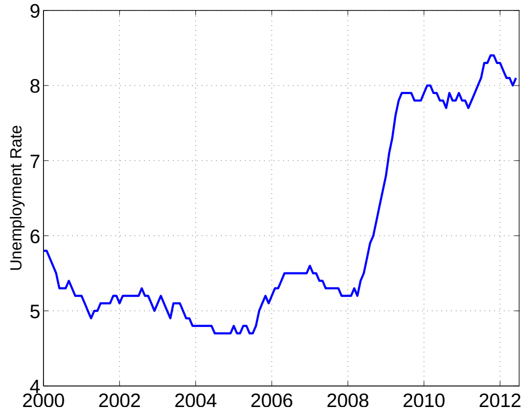


Figure 1: Unemployment Rate in the U.K.

1 Introduction

Figure 1 shows the evolution of the unemployment rate in the U.K. The U.K. unemployment rate hovered around 5% from 2000 to 2007 and increased to above 8% during the global recession and remained persistently high.

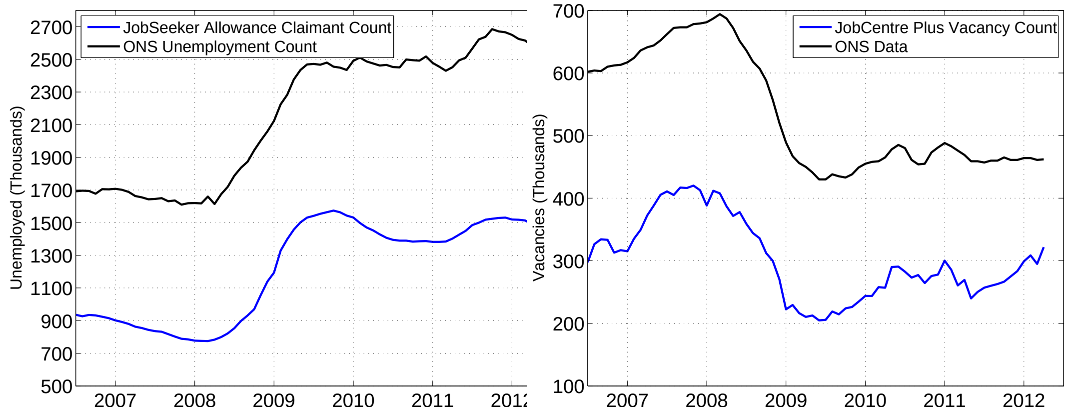
We apply the methodology developed by Sahin, Song, Topa and Violante (2013) to the U.K. labor market. Constructing our indexes requires detailed information on vacancies and unemployment counts by "labor market". For the U.K., we make use of the administrative data collected by local employment agencies. The vacancy stocks and flows come from Jobcentre Plus Vacancy Statistics and the unemployment counts are from Jobseeker's Allowance Claimant Counts and are available, starting in 2005 at a monthly basis, for 2-, 3-, 4-digit occupation codes and for different travel-to-work areas (TTWAs).

Our main findings are as follows. In the U.K. labor market, there is no evidence of a worsening in geographical mismatch. At the occupational level, instead, mismatch rose sharply during the recession, but then quickly fell towards a value slightly higher than its pre recession level before rising again through 2011.

The rest of the paper is organized as follows. Section 2 describes the main data sources. Section 3 discusses the specification of the matching function. Section 4 presents the main results. Section 5 extends the analysis to endogenous vacancy creation. Section 6 concludes.

2 Data Description

Our analysis requires detailed information on vacancies and unemployment. In particular, for each labor market we consider, we need monthly vacancy and unemployment statistics.



(a) Unemployed

(b) Vacancies

Figure 2: Aggregate Unemployment and Vacancies in the U.K.

We make use of the administrative data collected by local employment agencies that are available through Nomis.[1] The vacancy stocks and flows come from Jobcentre Plus Vacancy Statistics and the unemployment counts are from Jobseeker's Allowance Claimant Counts.[2] Both the vacancy and unemployment stocks and flows are available starting in 2005 on a monthly basis. The administrative data have the advantage of being available at a regular basis and at a disaggregated level which is ideal for the analysis of mismatch. The only drawback of the data is its coverage. Not all vacancies are reported to the Jobcentres and not all unemployed qualify or choose to collect jobseekers' allowance. Thus employers and workers who do not use Jobcentres as one of their search channels are not captured by the administrative data.

The left panel of Figure 2 shows the total number of claimants together with the number of unemployed measured by the Labor Force Survey. As expected, survey-based unemployment is higher than claimant count unemployment since not all unemployed workers collect Job Seekers Allowance. The level of claimant count unemployment is about two thirds of labor force unemployment. However, the two measures are highly correlated with a correlation of 0.98. In the right panel, we plot the Jobcentre Plus's vacancy measure against the Office of National Statistics' (ONS) economy-wide survey-based vacancy measure. Like our measure of the unemployed, the Jobcentre vacancy measure lies below the ONS measure. However, the two series are also highly correlated with a correlation coefficient of 0.92.

[1] https://www.nomisweb.co.uk/Default.asp

[2] Pissarides (1986), Layard and Nickell (1986), Jackman and Roper (1987) all used published vacancy statistics notified to the Employment Service run by the Department of Employment for their analysis of mismatch for 1960s and 1970s. The vacancy data used in these studies can be thought of as the predecessor of the Jobcentre vacancy data. More recently, Coles and Smith (1996) and Burgess and Profit (2001) both used the Jobcentre data to estimate matching functions for TTWAs for the UK between 1985-1995.

Tables B2 and B3 in the Appendix show a breakdown of the aggregate measures along various dimensions. Table B2 shows that the administrative data sample is slightly younger than that in the Labor Force Survey and has a higher fraction of men. Before the recession, the unemployment duration distribution among the claimants was higher than in the Labor force survey. Since newly unemployed who expect to find a job easily would be less likely to claim benefits, we would expect to see more high-duration unemployed as we do in this sample. However, after the start of the recession, the duration distribution of the claimant moved down to very closely match the distribution in the labor fore survey, with around 50% of both samples being unemployed for less than 6 months. As individuals likely anticipate having more difficulty finding a job during recessions, they are more likely to claim benefits and enter our sample at a lower unemployment duration. Tables B3 shows that the JobCentre Plus vacancies are very highly concentrated in banking, finance, and insurance which alone represents 53% of the total number of vacancies. Compared with the survey-based measure, our sample also under-represents manufacturing and transportation.

In the administrative data, both unemployment and vacancy counts are available for 2-, 3-, and 4-digit occupation codes and for different TTWAs (travel-to-work areas).[3] Throughout our analysis, we focus on the following definitions of labor markets: 1) 2-digit level occupations; 2) 3-digit level occupations; 3) Regions;[4] 4) Travel To Work Areas (henceforth, TTWA's); 5) 2-digit level occupations and TTWA's. The first two definitions will enable us to study occupational mismatch; the third and fourth refer to geographic mismatch, and the last one defines a local labor market as a specific occupation in a given location. For the claimant counts by occupation, we classify searchers using their sought occupation. [5] We use unfilled live vacancies as our measure of stock of vacancies and the total Jobseeker claimant count as our measure of stock of unemployment. Both of these stocks are reported at the end of each month.

We start our analysis from July 2006. This choice is motivated by a change in Jobcentre Plus's vacancy handling procedure which was introduced in May 2006. In particular, prior to May 2006, vacancies notified to Jobcentre Plus were followed up with the employer to ascertain whether (a) they should remain available to jobseekers, or (b) they should be closed

[3]TTWAs are defined by the Office for National Statistics as zones that are labor market areas. The fundamental criterion is that, of the resident economically active population, at least 75% actually work in the area, and that, of everyone working in the area, at least 75% live in the area. 243 TTWAs were defined in 2007 by using 2001 Census data. See appendix table B1 for a list of the 2-digit occupation codes we use in our analysis

[4]See http://www.ons.gov.uk/ons/guide-method/geography/beginner-s-guide/index.html for more information on the definitions.

[5]We could also have used the usual occupation to classify claimants. The correlation between the two series is 0.99 on average across occupations and the average difference between the usual occupation and the sought occupation series is on average less than 2% of the total.

or had been filled by clients referred by Jobcentre Plus. Starting from May 2006 vacancies notified to Jobcentre Plus have a fixed closure date. Vacancies are automatically withdrawn on the closure date unless the employer advises that a later closure date is required. Due to this change, there is a sharp decline in the number of live unfilled vacancies in May 2006. In the sample we use there are a few other discontinues that we take into account.[6]

For the estimation of the matching function, we need a measure of total matches formed within a month. In the administrative data, we have two potential measures of hires. One potential measure is the total *vacancy outflows* which measures the total number of live vacancies which disappear each month. This measure would assume that all vacancies that flow out of the sample are filled by unemployed seekers. This assumption is unlikely to hold given that some vacancies are filled by employed or nonparticipant workers. An alternative measure of total matches is total *claimant off-flows*, which measures the number of claimants who exit the sample each month.[7] This measure of matches would assumes that all unemployed who leave the sample do so because they find jobs. This assumption is also unlikely to hold as people can stop claiming Jobseeker benefits to various reasons other than finding a job.[8] While both of these measures and subject to measurement error, there is no reason to think that the errors are correlated and therefore we use the average of the two outflow series as our measure of matches.[9]

As a measure of productivity, we use mean hourly wages by occupation and TTWA from Annual Survey of Hours and Earnings (ASHE). We calculate job-destruction rates using data from the Labor Force Survey. We utilize the quarterly matched sample surveys and compute employment to unemployment transition rates at the 2-digit occupation level. See Figure B2 in the Appendix for plots of productivity and job-destruction rates of selected occupations.

[6] Starting in March 2007, ONS added UK armed forces vacancies into the data under “Protective Service Occupations” (SOC = 33) and “Protective Service Officers” (SOC=117). This caused approximately a tenfold increase in the number of vacancies in these occupations. Also, all the UK armed forces vacancies were allocated to the “Lincoln” Travel to Work Area. To address this issue, we have excluded these occupations and geographical area from our analysis. Lastly, there was an irreconcilable spike in vacancy outflows for “administrative occupations: government and related organizations” (SOC=411) in May 2009. We impute the May 2009 value by taking the average of April 2009 and June 2009. The aggregate 2-digit occupation code (SOC=41) was also imputed for May 2009 in the same way. Lastly, the claimant and vacancy counts are missing for September 2010 so we again interpolate the September 2010 value by taking the average of August 2010 and October 2010.

[7] This measure is similar to the unemployment outflow measure used in Shimer (2005).

[8] While the Jobseeker data does include information on the reason for exiting the sample, the percentage of off-flows with a “not known” or “failed to sign” destination has increased significantly since the start of the series (representing 45% of total UK off-flows in June 2012) as the completion levels of the forms filled in by Job Seekers’s Allowance leavers decreased significantly over the sample period. This complicates the interpretation of the series and the decline in the job-finding rate over the recession.

[9] See Appendix Figure B1 for a plot of the various hires measures and Table B5 for the results of the matching function estimation using the various measures.

	OLS	GMM	Sample Size
Aggregate	0.559^{***}	–	72
	(0.059)	–	
ϕ_i Fixed	0.472^{***}	–	1728
	(0.006)	–	
ϕ_i Varying	0.463^{***}	–	1728
	(0.006)	–	

Table 1: OLS and GMM estimates of the vacancy share α using aggregate and 2-digit occupation panel data. S.E. in parenthesis. See Section 3 for details.

Lastly, for the calculation of the counterfactual unemployment, we calculate job-finding and separation rates using aggregate data from Eurostat. We linearly interpolate monthly counts from quarterly measures of total unemployment, unemployed for less than 1 month, and total employment.

3 Matching function specification

We start by showing that a matching function with unit elasticity is a reasonable representation of the hiring process at the sectoral level. For the 2-digit occupation definition of sectors[10] and the period July 2006-June 2012, we estimate the parameters of the following CES matching function via minimum distance:[11]

$$\ln\left(\frac{h_{it}}{u_{it}}\right) = \ln\phi_i + \frac{1}{\sigma}\ln\left[\alpha\left(\frac{v_{it}}{u_{it}}\right)^{\sigma} + (1-\alpha)\right]. \tag{1}$$

Recall that $\sigma \in (-\infty, 1)$ with $\sigma = 0$ being the Cobb-Douglas case.[12]

In Table 1, we report the estimation results of various regressions for a Cobb-Douglas matching function. At the aggregate level, we estimate a function of the form

$$\ln\left(\frac{h_{it}}{u_{it}}\right) = const + \gamma' QTT_t + \alpha\ln\left(\frac{v_{it}}{u_t}\right) + \epsilon_t, \tag{2}$$

[10]This includes 23 occupations after dropping protective service occupations for reasons discussed in Section 2

[11]Note that to be consistent with the timing of the measurement of flows and stocks, we use the unemployment and vacancy stocks at the beginning of the month (which are given by the stocks in month t-1) and the vacancy flows during the month (which are given by flows in month t) in all regressions throughout the paper.

[12]The estimation is performed by simulated annealing to ensure what we obtain is a local minimum. Results are very robust to the weighting matrix used.

where QTT_t is a vector of four elements for the quartic time trend.[13] At the sectoral level, we estimate a panel regression of the following form:

$$\ln\left(\frac{h_{it}}{u_{it}}\right) = \gamma' QTT_t + \chi_{t<=3/08} \ln \phi_i^{pre} + \chi_{t>3/08} \ln \phi_i^{post} + \alpha \ln\left(\frac{v_{it}}{u_{it}}\right) + \epsilon_t, \qquad (3)$$

where we fix the vacancy share α to be constant across markets and over time. We estimate the regression using 2-digit occupations and report results both for the model where ϕ_i is allowed to vary across sectors and for the model where it is restricted to be the same. We also run an aggregate level regression. As Table 1 shows, the estimates for α, the elasticity of hires with respect to vacancies, range from 0.45 to 0.56 depending on the restriction on ϕ. We choose the value $\alpha = 0.5$ which is in the middle of the range and it is also the value that typically produces the highest estimates for mismatch.[14]

Table B4 reports the estimates for the sectoral matching efficiency parameters ϕ_i. Higher matching efficiency may be the result of a variety of factors such as looser skill requirements or differential use of informal hiring methods that make matching workers to vacancies intrinsically easier in certain jobs.[15] Because of changes in matching efficiency over the business cycle, we estimate a pre- and post- recession ϕ. In all our calculations, we use pre-recession estimates of sectoral matching efficiency.[16]

Overall, we do not uncover a large heterogeneity in estimates of ϕ_is. Secretarial (administrative) and customer service occupations have the largest ϕ_i, while arts, leisure (sports), personal care and science and technology professional occupations are those with the smallest ϕ_i. One interpretation of these differences is that general skill labor markets have the highest ϕ_i and specialized skill labor markets the lowest ϕ_i.

4 Results

4.1 Occupational Mismatch

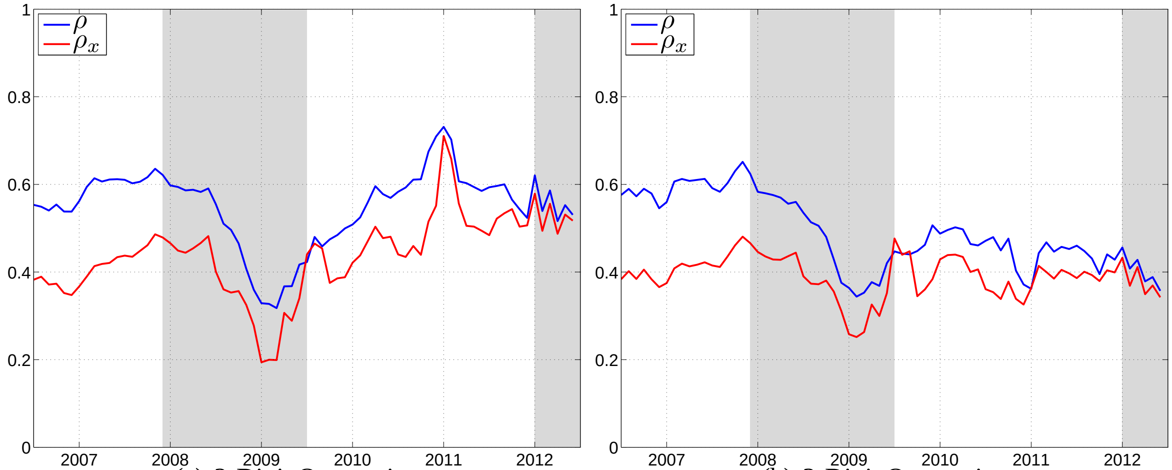
Because the definition of mismatch in section **??** implies a close relationship between the mismatch indices and the correlation between the unemployment and vacancy shares, it is

[13] There was a notable drop in the measured match efficiency in the U.S. during the Great Recession as documented by various studies. We include a quartic time trend for the U.K. to capture the potential shift in aggregate matching efficiency through the recent recession similar to Sahin, Song, Topa, and Violante (2011).

[14] Sahin, Song, Topa and Violante (2013) find similar estimates for alpha in the estimation of the same matching function using U.S. data. See Appendix Figure B6 for the results of the index using various values of alpha.

[15] See Davis, Faberman and Haltiwanger (2010), for a discussion on the sources of heterogeneity in vacancy yields.

[16] However, we check the robustness of this choice and find that the results are not sensitive to this choice.



(a) 2-Digit Occupation (b) 3-Digit Occupation

Figure 3: The correlation coefficient between vacancy and unemployment shares across occupations.

useful to first examine the simple correlation across vacancy and unemployment shares. The planner's allocation rule would result in a perfect correlation between unemployment shares and appropriately weighted vacancy shares across sectors. Therefore, a correlation coefficient below 1 signals the presence of mismatch. Figure 3 shows correlation coefficients across the two series over our sample period for both 2-digit (left panel) and 3-digit (right panel) occupations. The blue line ρ is the simple correlation between unemployment shares (u_{it}/u_t) and vacancy shares (v_{it}/v_t) and the red line ρ_x shows the correlation between unemployment shares (u_{it}/u_t) and weighted vacancy shares $(x_i/\bar{x}_t)^{1/\alpha}(v_{it}/v_t)$. In both series, there is an obvious sharp drop during the 2008 recession, a recovery during 2010 and 2011 and a mild drop in the early part of 2012[17]

The left panels of Figure 4 shows the unadjusted mismatch index M_t and the version of the index adjusted for heterogeneity M_{xt} across 2- and 3- digit occupations.[18] As suggested by Figure 3, this figure shows that the fraction of hires lost because of misallocation of unemployed workers across 2-digit occupations increased significantly during the recession,

[17]To get a sense of which occupations are contributing to changes in correlation, see Appendix Figure B3, which plots the vacancy and unemployment shares for selected 2-digit occupations. The left panel shows that unemployment shares were relatively flay through 2007 but showed a marked dispersion through 2008, as occupations such as construction and corporate managers saw a rise in their unemployment share while sectors like customer service and science and technology did not. Simultaneously, the vacancy shares of construction and customer service fell sharply while that of science and technology and corporate managers remained fairly stable through the 2008 recession. As mismatch by our definition is driven by a dispersion in the experiences across sectors, the visible variation in the vacancy and unemployment shares is illustrative.

[18]All Indices reported in this paper have been HP-filtered ($\lambda = 10$) to eliminate high-frequency movements in the series.

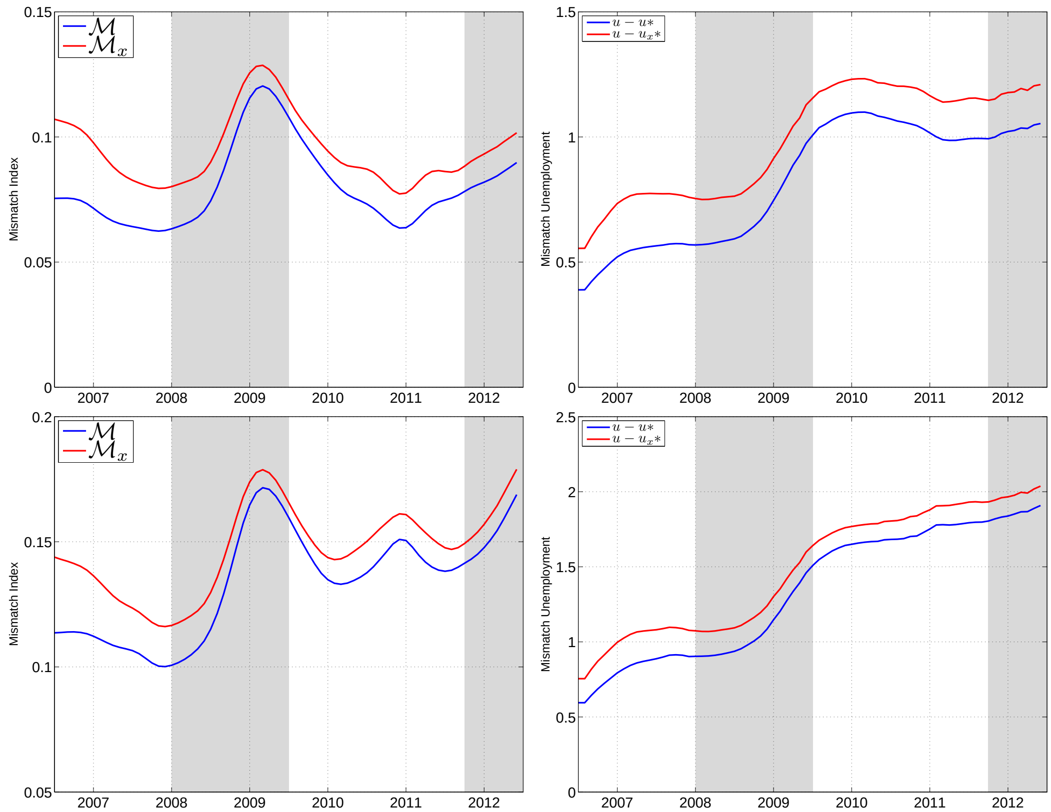


Figure 4: Mismatch Indexes M_t and M_x and corresponding mismatch unemployment rates for 2-Digit (top) and 3-Digit (bottom) Occupations.

rising from 4 to 7 percentage points, depending on the index used. The efficiency-weighted index, M_{xt}, is higher than the unadjusted index at both the 2- and 3- digit level.[19] However, the rise in the adjusted index over the 2008 recession is smaller than that in the unadjusted index.[20]

The right panels of Figure 4 plots the corresponding mismatch unemployment rates, which are the difference between the actual and the counterfactual unemployment rate that would have been observed in the absence of mismatch. It is clear that mismatch unemployment rose sharply in the recession in 2009. While mismatch unemployment fell as the index came down through 2011, it rose again in 2012 as the U.K. slipped into another recession and the mismatch index back up.

Table 2 shows the change in mismatch unemployment over the 2008 recession. We show

[19]For the 3-digit index, we apply the 2-digit ϕ and δ estimates to all 3-digit occupations within that classification.

[20]See Figures B4 and B5 in the Appendix for indices with isolated sources of heterogeneity - M_ϕ, M_z, and M_δ. This shows that the different matching efficiencies across occupations has the largest effect on the index, which dispersion in destruction rates and productivity have very little effect.

	Index	$u_{08.Q1} - u^*_{08.Q1}$	$u_{10.02} - u^*_{10.02}$	$\Delta(u - u^*)$	$\Delta(u - u^*)/\Delta u$
2-digit Occupation	$\mathcal{M}$	0.57	1.10	0.53	18.9%
	$\mathcal{M}_x$	0.75	1.23	0.48	17.1%
	$\mathcal{M}_x^{v^*}(\varepsilon = 0.5)$	1.62	2.78	1.16	41.2%
	$\mathcal{M}_x^{v^*}(\varepsilon = 1.0)$	1.21	2.09	0.88	31.5%
	$\mathcal{M}_x^{v^*}(\varepsilon = 2.0)$	0.98	1.68	0.70	25.1%
3-digit Occupation	$\mathcal{M}$	0.90	1.66	0.75	26.9%
	$\mathcal{M}_x$	1.07	1.77	0.70	25.2%
Routine/Cognitive	$\mathcal{M}_{RC}$	0.13	0.49	0.36	12.8%
Region	$\mathcal{M}$	0.15	0.22	0.07	2.6%
TTWA	$\mathcal{M}$	0.27	0.30	0.03	1.2%
	$\mathcal{M}_z$	0.26	0.29	0.03	1.2%
TWAx2-digit Occupation	$\mathcal{M}$	0.95	1.54	0.59	21.2%

Table 2: Changes in mismatch unemployment for occupation and geographic mismatch. All the differences are calculated as the difference between February 2010 and the first quarter of 2008. Note that $\Delta u = 2.8$ percentage points.

the change in mismatch unemployment February 2010 to the average of the the first quarter of 2008.These dates are chosen to reflect the movements in the overall unemployment rate. Unemployment was at a pre-recession low of 5.2% in the first quarter of 2008 and peaked after the first recession in February 2010 at 8%. The unemployment rate then held steady through 2010 averaging 7.9% but ticked up again to a new peak of 8.4% in November 2011. See Figure 1. Throughout the paper, we will refer to changes over these two periods when we discuss the role of mismatch through the recessions.

Related to a rise in mismatch across occupations is the notion of job-polarization, which refers to the increasing concentration of employment in the highest and lowest skill occupations and a hollowing out of opportunities in middle skill occupations. [21]To explore the effect of job-polarization on the behavior of our measured mismatch, we group the 2-digit occupations into 4 categories following Acemoglu and Autor (2011): routine cognitive, routine manual, non-routine cognitive and non-routine manual.[22].Figure 5 plots this ”Routine/Cognitive” index - denoted M_{RC} - against the full 2-digit index and the corresponding mismatch unemployment rates. We find evidence of mismatch across these skill categories which, like the overall 2-digit occupation index, rose during the 2008 recession, explaining around 13% of the rise in the overall unemployment rate. This finding suggests that the differences in vacancy and unemployment shares across these four skill groups account for

[21]Job-polarization in the U.K has been documented by Good, Manning and Salomons (2011) https://lirias.kuleuven.be/bitstream/123456789/331184/1/DPS1134.pdf

[22]See Table B1 for classification of 2-digit occupations.

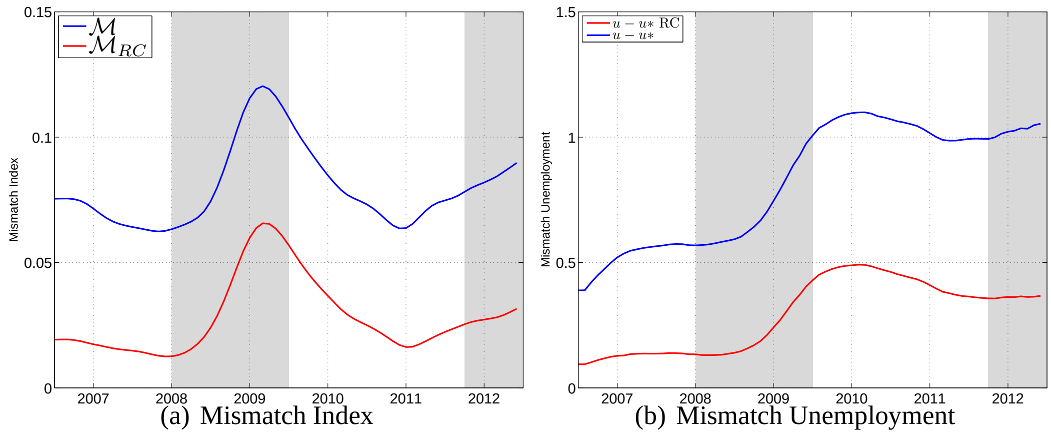


Figure 5: Mismatch Index M_{RC} calculated across 4 Routine-Cognitive Occupation groups and the corresponding mismatch unemployment.

about two thirds of the total rise in occupational mismatch while the rest occurred within these four categories.

4.1.1 Low wage vs high wage sectors

In our benchmark, we took the view that planner can freely move unemployed workers across all sectors. At the other end of the spectrum, one could assume that mobility is costless only between sectors of similar skill levels, but it is infinitely costly between skill levels. Then, the economy would feature segregated labor markets and a different planner problem would apply to each skill level.

As a first step, we explore this idea by studying mismatch separately for high- vs. low-productivity occupations, using wages as a proxy for productivity. We compute median and mean hourly and weekly gross wages for our 2-digit occupational categories over our sample period. We then divide the twenty four 2-digit occupations into high and low-wage occupations using the median across these occupations as a threshold.

Figure 9 plots $\mathcal{M}_t^u$ separately for these two groups. For the high wage group, we find a more substantial increase and, interestingly, a more persistent one. While mismatch for the low wage occupations goes back to its pre recession level, in the high wage ones, it is still almost twice as large.[23] Figure 10 and 11 report the contributions of specific occupations to mismatch for each wage group, plotting $(u_{it}/u_t - v_{it}/v_t)$ over time. In the high wage group, "Skilled Construction and Building Trades" and "Health and Social Welfare Asso-

[23]In the next version of the paper, we will report a calculation of the fraction of the rise in unemployed due to mismatch for both skill groups. It is likely that we'll conclude that mismatch is extremely important for high-skilled workers unemployment dynamics.

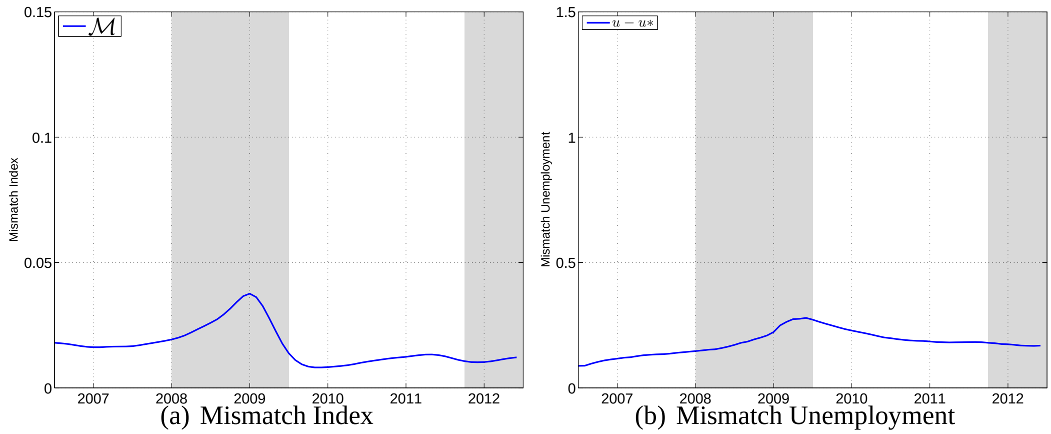


Figure 6: Mismatch Index M_t calculated across Regions and the corresponding mismatch unemployment.

ciate Professionals" are causing the spike during the recession, but for opposite reasons. In the low wage group, the "Caring Personal Service" and "Elementary Administrative and Services" occupations are driving the temporary spike, but they quickly return back to their pre-recession levels of unemployment-vacancy share differential.[24]

4.2 Geographical Mismatch

We explore the role of mismatch across geographic areas at two levels of disaggregation. First, we look at the mismatch across the 9 regions within England. Figure 6 shows the mismatch index M_t by region and the corresponding mismatch unemployment rate. We find that before the recession, mismatch across these 9 regions is very small and accounts for only about 2 percent of hires lost. Additionally, the index rose minimally during the 2008 recession, explaining only around 3% of the rise in the overall unemployment rate.

Secondly, we perform our analysis across Travel-to-Work Areas (TTWA) both in the aggregate and across 2-digit occupations within TTWA. We include only markets for which there are more than 10 vacancies for each month within our sample period, leaving us with 215 TTWAs and 1,059 occupation within TTWA groups. The top two panels of Figure 7 shows the mismatch index M_t by TTWA and the corresponding mismatch unemployment rate. We find that mismatch across the TTWAs played a negligible role in the 2008 recession and in fact, the index fell through 2008 and 2009. The bottom two panels of the Figure

[24]"Health and Social Welfare Associate Professionals" are nurses, doctors, therapists and social welfare workers. "Caring Personal Service" are assistant nurses, dental nurses, orderlies, ambulance drivers (excluding paramedics), child care and animal care providers. The latter group is less skilled than the former, perhaps making it easier to fill vacancies.

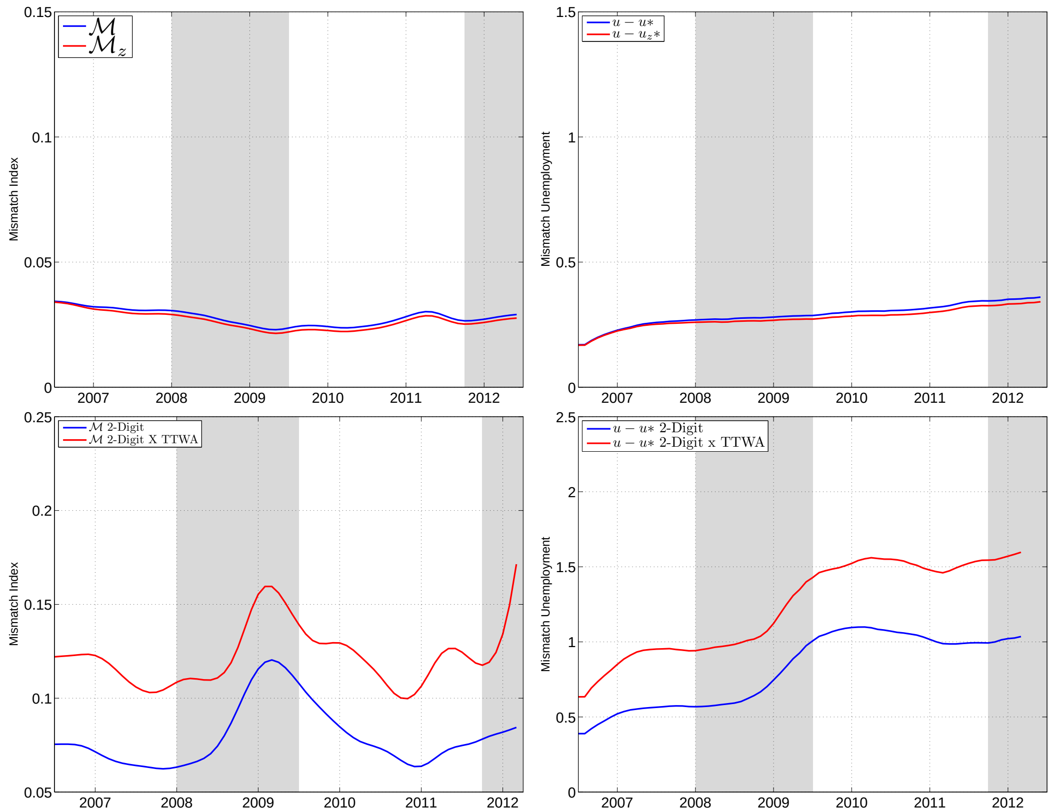


Figure 7: Top Panel: Mismatch Index M_t and M_z for TTWA and corresponding mismatch unemployment rates. Bottom Panel: Mismatch Index M_t and at the 2-digit occupation in the aggregate and within TTWA and corresponding mismatch unemployment rates.

7 shows the index and corresponding mismatch unemployment rate for the combination of location and occupation. We find that while this index is higher than the 2-digit occupation index, it evolved very similarly and as shown in table 2 implies a similar role of mismatch over the 2008 recession. Taken together, this analysis implies that geographic mismatch was an insignificant factor in the recent dynamics of the unemployment rate in the U.K.

4.3 Double Dip Recession

While we have focused in this discussion mainly on the 2008 recession, when there was the largest increase in the overall unemployment rate, mismatch continued to play a similar role as the UK slipped back into a recession in early 2012. Figure 4 clearly shows that although mismatch fell during the recovery trough 2010, occupational mismatch rose again through 2011 and 2012 as the overall unemployment rate ticked upwards again. Table 3 reports the changes in mismatch over the both recessions, comparing mismatch unemployment rates in November 2011, when the overall unemployment rate peaked, to the first quarter of 2008. We

	Index	$u_{08.Q1} - u^*_{08.Q1}$	$u_{11.11} - u^*_{11.11}$	$\Delta(u - u^*)$	$\Delta(u - u^*)/\Delta u$
2-digit Occupation	$\mathcal{M}$	0.57	0.99	0.43	13.4%
	$\mathcal{M}_x$	0.75	1.15	0.39	12.5%
	$\mathcal{M}_x^{v^*}(\varepsilon = 0.5)$	1.62	2.66	1.04	32.5%
	$\mathcal{M}_x^{v^*}(\varepsilon = 1.0)$	1.21	1.94	0.73	22.9%
	$\mathcal{M}_x^{v^*}(\varepsilon = 2.0)$	0.98	1.55	0.57	17.8%
3-digit Occupation	$\mathcal{M}$	0.90	1.82	0.91	28.6%
	$\mathcal{M}_x$	1.07	1.95	0.87	27.3%
Routine/Cognitive	$\mathcal{M}_{RC}$	0.13	0.35	0.22	7.0%
Region	$\mathcal{M}$	0.15	0.18	0.03	0.9%
TTWA	$\mathcal{M}$	0.27	0.35	0.08	2.2%
	$\mathcal{M}_z$	0.26	0.32	0.07	2.1%
TWAx2-digit Occupation	$\mathcal{M}$	0.95	1.55	0.60	18.7%

Table 3: Changes in mismatch unemployment for occupation and geographic mismatch. All the differences are calculated as the difference between November 2011 and the first quarter of 2008. Note that $\Delta u = 3.2$ percentage points.

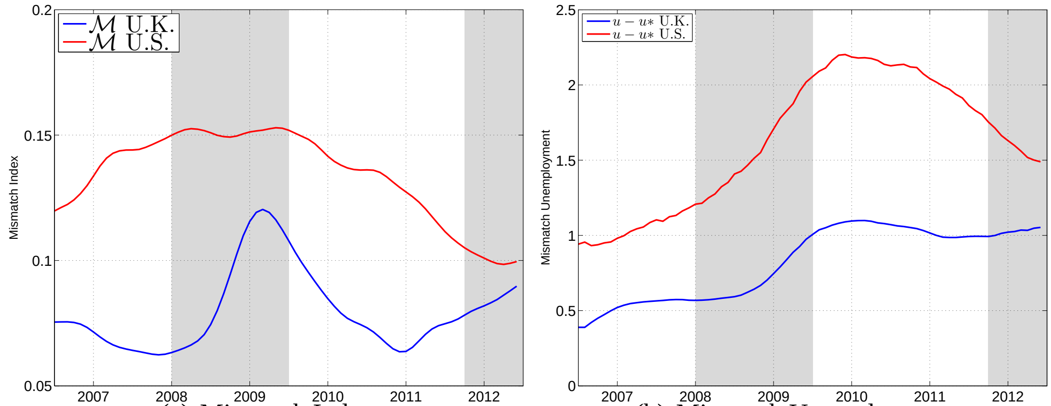
see that while the role of mismatch across occupations decreased slightly during the recovery in 2010, occupational mismatch continued to explain upwards of 10% of the overall rise in the unemployment rate. As before, geographical mismatch continued to play a negligible role in explaining the unemployment dynamics.

4.4 How does the U.K compare to the U.S?

Figure 8 plots the 2-digit occupation M_t index from Figure 4 alongside a 2-digit occupation index calculated for the U.S. as described in Sahin, Song, Topa and Violante (2013). The figures reveal that role of mismatch in the two countries differs in three ways. First, over the entire sample period, the level of mismatch was higher in the U.S. than in the U.K. Secondly, while the U.K. saw a steep rise in the role of mismatch through the 2008 recession and a subsequent quick drop through 2009, the U.S. experienced a more gradual rise and fall in mismatch through the recession. Third, while mismatch levels and the resulting mismatch unemployment rate in the U.S. has been declining steadily since its peak in 2009, mismatch in the U.K. rose again through 2011 and 2012 as the U.K. experienced a second recession.

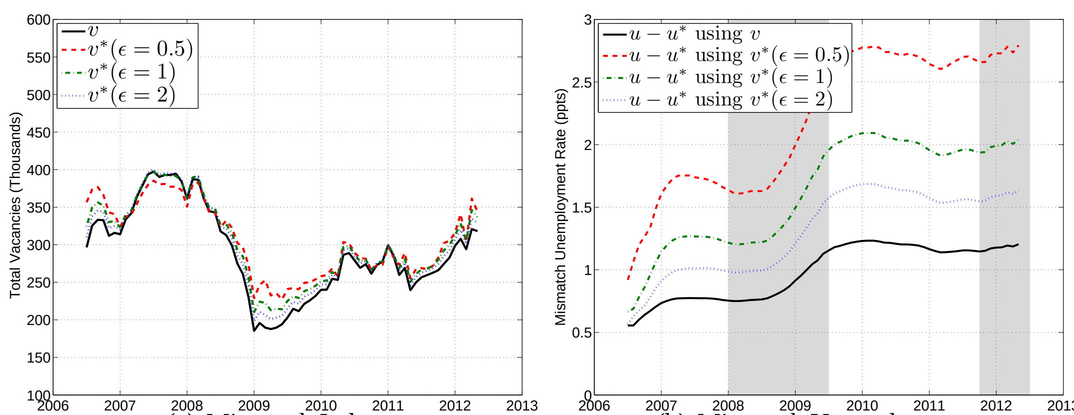
5 Endogenous Vacancies

In this section, we show the results of our analysis if we relax the assumption that the distribution of vacancies is endogenous.



(a) Mismatch Index (b) Mismatch Unemployment

Figure 8: Mismatch Index M_t calculated across 2-digit occupations in the U.K and U.S and the corresponding mismatch unemployment rates. Recession shading marks periods of negative growth in the U.K.



(a) Mismatch Index (b) Mismatch Unemployment

Figure 9: Mismatch Index M_t calculated across 2-digit occupations in the U.K and U.S and the corresponding mismatch unemployment rates.

Figure 9 shows the results across 2-digit occupations. The left panel plots aggregate vacancies v_t^* in the planner's economy for different values of ε and the right panel shows the corresponding mismatch unemployment rates. Table 2 shows that the contribution of mismatch to the rise in the unemployment for the endogenous vacancies case. The contribution of mismatch is higher for the $\varepsilon = 0.5$ case but still explains only around one third of the rise in the unemployment rate.

6 Conclusions

This paper collects work in progress where we are attempting to formalize and measure the notion of mismatch unemployment. This concept has recently become central to the macro policy debate. We find that in the U.K¿ labor market mismatch has worsened across occupations but not geographical areas, and that at most it can account for 1/3 of the recession-driven rise in unemployment. Our findings indicate that imbalances between vacancies and unemployed workers may be much more important for skilled (high wage) occupations.

References

Code	Occupation	Classification
11	Corporate Managers	Cognitive/Non-routine
12	Managers and Proprietors in Agriculture and Services	Cognitive/Non-routine
21	Science and Technology Professionals	Cognitive/Non-routine
22	Health Professionals	Cognitive/Non-routine
23	Teaching and Research Professionals	Cognitive/Non-routine
24	Business and Public Service Professionals	Cognitive/Non-routine
31	Science and Technology Associate Professionals	Cognitive/Non-routine
32	Health and Social Welfare Associate Professionals	Cognitive/Non-routine
34	Culture, Media and Sports Occupations	Cognitive/Non-routine
35	Business and Public Service Associate Professionals	Cognitive/Non-routine
41	Administrative Occupations	Manual/Non-routine
42	Secretarial and Related Occupations	Manual/Non-routine
51	Skilled Agricultural Trades	Manual/Routine
52	Skilled Metal and Electronic Trades	Manual/Routine
53	Skilled Construction and Building Trades	Manual/Routine
54	Textiles, Printing and Other Skilled Trades	Manual/Routine
61	Office and Administrative Support Occupations	Cognitive/Routine
62	Leisure and Other Personal Service Occupations	Cognitive/Routine
71	Sales Occupations	Manual/Non-routine
72	Customer Service Occupations	Manual/Non-routine
81	Process, Plant and Machine Operatives	Manual/Routine
82	Transport and Mobile Machine Drives and Operatives	Manual/Routine
91	Elementary Trades, Plant and Storage Related Occupations	Manual/Routine
92	Elementary Administration and Service Occupations	Manual/Non-routine

Table B1: 2-digit occupation codes used in our empirical analysis. The classification in the right column is used in Figure 5.

	Labor Force Survey		Claimant Count	
	Pre-Recession	Post-Recession	Pre-Recession	Post-Recession
Age				
16-24	0.42	0.39	0.42	0.35
25-49	0.43	0.45	0.52	0.57
50+	0.14	0.15	0.07	0.08
Gender				
Male	0.57	0.59	0.73	0.71
Female	0.43	0.41	0.27	0.29
Duration				
under 6 months	0.60	0.52	0.47	0.54
6-12 months	0.16	0.19	0.21	0.21
12-24 months	0.13	0.16	0.16	0.14
24+ months	0.11	0.13	0.17	0.12

Table B2: Comparison of claimant counts to survey-based unemployment measures from the Labor Force Survey.

	Vacancy Survey		JobCentre Plus	
	Pre-Recession	Post-Recession	Pre-Recession	Post-Recession
Industry				
Energy and Water	0.01	0.01	0.01	0.01
Manufacturing	0.09	0.07	0.03	0.03
Construction	0.04	0.03	0.03	0.03
Distribution, Hotels& Restaurants	0.28	0.28	0.17	0.13
Transport and communications	0.11	0.10	0.04	0.03
Banking, Finance & Insurance	0.23	0.21	0.57	0.53
Public Administration, Education & Health	0.21	0.24	0.12	0.20
Other Services	0.04	0.04	0.04	0.05

Table B3: Comparison of JobCentre Plus vacancies across industries to survey-based vacancy counts from the ONS. Classifications are based on aggregated 2003 SIC codes.

2-Digit Occupation	ϕ^{pre}	ϕ^{post}
Corporate Managers	0.49	0.43
Managers and Proprietors in Agriculture and Services	0.47	0.41
Science and Technology Professionals	0.44	0.42
Health Professionals	0.56	0.51
Teaching and Research Professionals	0.50	0.48
Business and Public Service Professionals	0.50	0.45
Science and Technology Associate Professionals	0.46	0.42
Health and Social Welfare Associate Professionals	0.53	0.45
Culture, Media and Sports Occupations	0.43	0.41
Business and Public Service Associate Professionals	0.66	0.57
Administrative Occupations	0.55	0.50
Secretarial and Related Occupations	0.65	0.56
Skilled Agricultural Trades	0.46	0.47
Skilled Metal and Electronic Trades	0.48	0.45
Skilled Construction and Building Trades	0.51	0.54
Textiles, Printing and Other Skilled Trades	0.46	0.40
Office and Administrative Support Occupations	0.43	0.40
Leisure and Other Personal Service Occupations	0.45	0.40
Sales Occupations	0.44	0.40
Customer Service Occupations	0.67	0.49
Process, Plant and Machine Operatives	0.44	0.42
Transport and Mobile Machine Drives and Operatives	0.44	0.40
Elementary Trades, Plant and Storage Related Occupations	0.50	0.49
Elementary Administration and Service Occupations	0.49	0.41

Table B4: Estimates of occupation-specific match efficiencies using average outflows.

	Aggregate	ϕ_i Fixed	ϕ_i Varying
Vacancy Outflows	0.854^{***}	0.813^{***}	0.804^{***}
	(0.070)	(0.007)	(0.014)
Claimant Outflows	0.210^{***}	0.076^{***}	0.103^{***}
	(0.054)	(0.004)	(0.007)
Average Outflows	0.559^{***}	0.472^{***}	0.463^{***}
	(0.060)	(0.006)	(0.011)

Table B5: OLS estimates of the vacancy share α using aggregate and 2-digit occupation panel data. S.E. in parenthesis. See Section 3 for details.

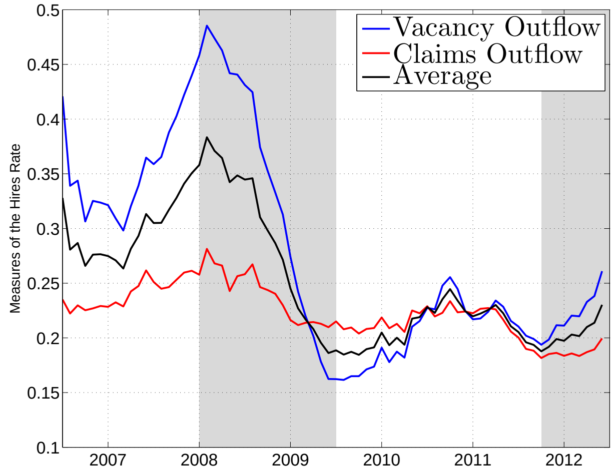


Figure B1: Time series of various measures of matches.

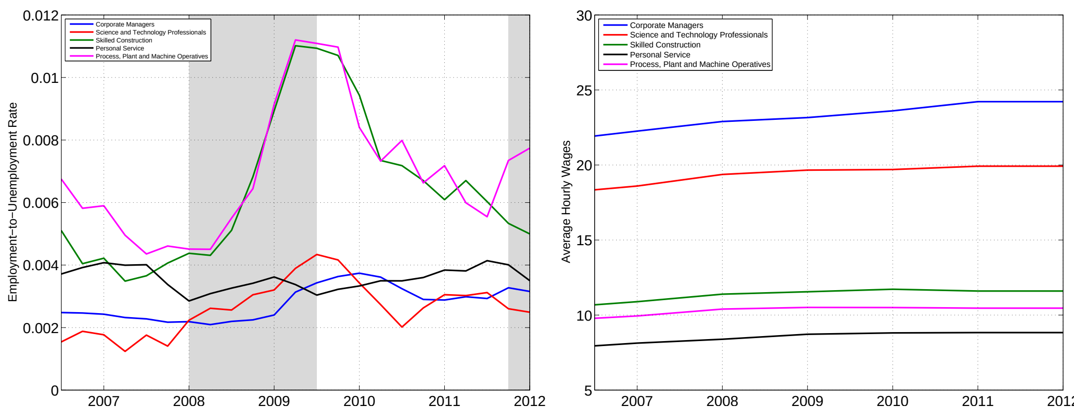
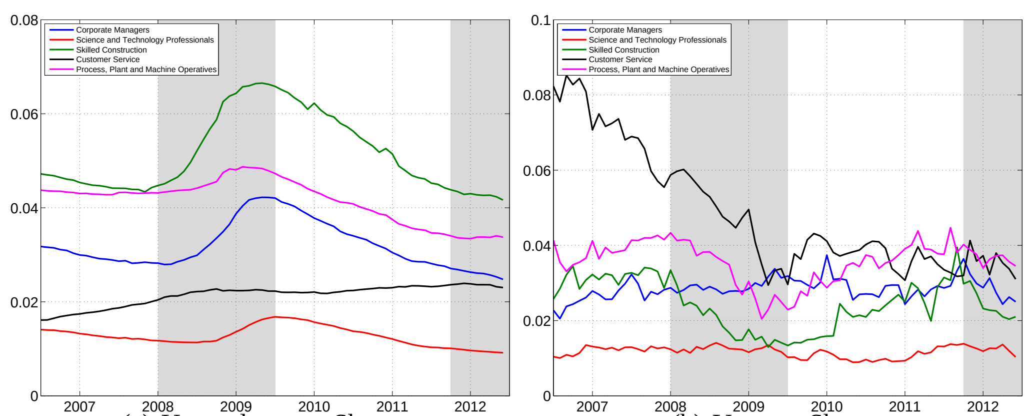


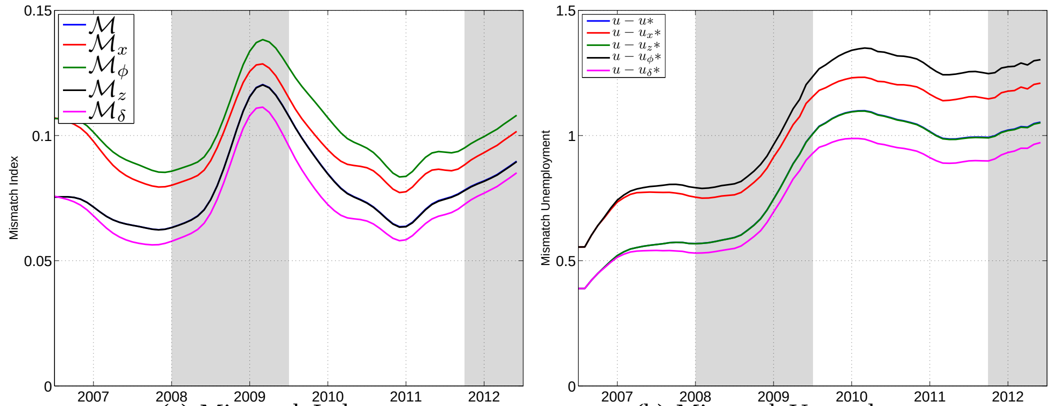
Figure B2: Job destruction rates (left) and average hourly wages (right) for selected occupations



(a) Unemployment Shares

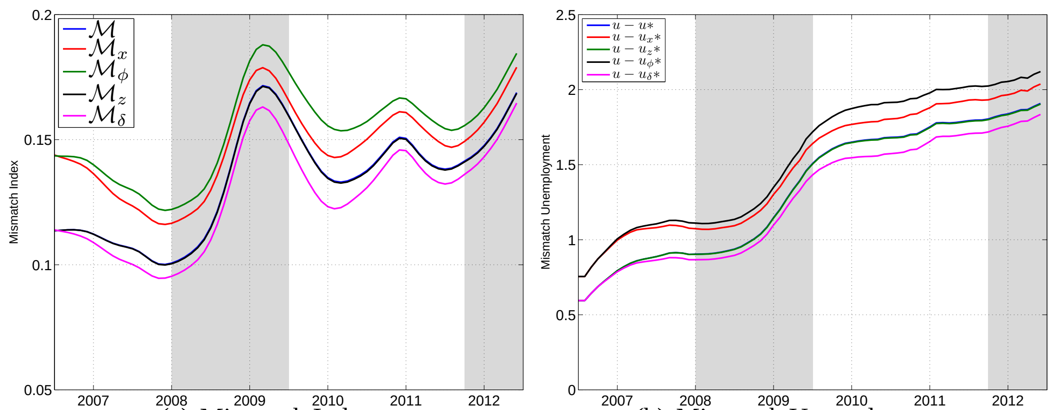
(b) Vacancy Shares

Figure B3: Unemployment and Vacancy Shares for selected matched occupations.



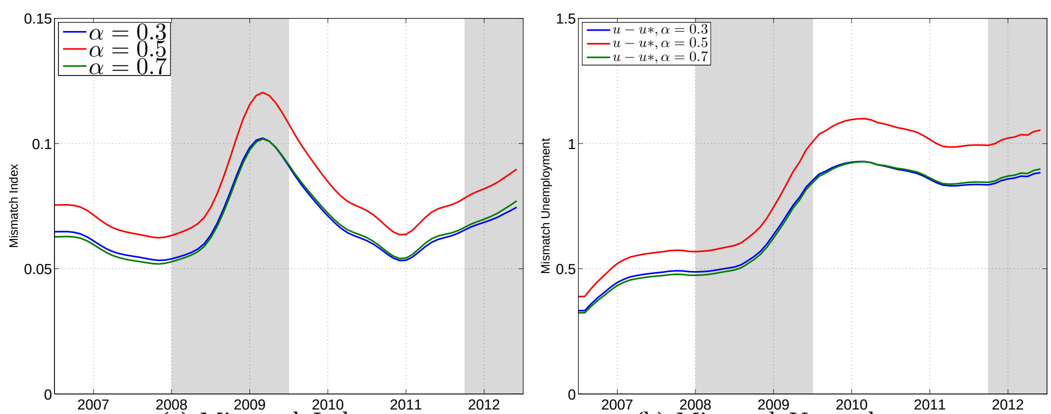
(a) Mismatch Index (b) Mismatch Unemployment

Figure B4: Mismatch Indices M, M_x, M_ϕ, M_z and M_δ across 2-Digit Occupations and the corresponding mismatch unemployment rates.



(a) Mismatch Index (b) Mismatch Unemployment

Figure B5: Mismatch Indices M, M_x, M_ϕ, M_z and M_δ across 3-Digit Occupations and the corresponding mismatch unemployment rates.



(a) Mismatch Index (b) Mismatch Unemployment

Figure B6: Mismatch Indices M_t and corresponding mismatch unemployment rates for various values of alpha.