Unemployment and Mismatch in the UK

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This version: April 2013. First version: May 2012

Abstract
The extent of misallocation in the UK labour market is measured and its impact on unemployment dynamics is estimated. Measures of mismatch across industry, occupation and region paint a varied picture. However, all are estimated to have had a substantial impact on UK unemployment behaviour. Overall, mismatch appears responsible for around half the UK unemployment rise during 2008-09. Although on some measures mismatch has returned to normal levels, its impact on the UK unemployment rate persists.

Keywords: Unemployment, Unemployment Dynamics, Mismatch, Matching Efficiency.

JEL codes: J6, E24, E32.

* I should like to thank Pedro Gomes, Bob Hall, Chris Pissarides, Thijs van Rens and participants at the Chief Economists’ Workshop on Labour Market Dynamics during the Financial Crisis, Bank of England, May 2012, the Bank of England/Institute of Macroeconomics Conference on Unemployment, Productivity and Potential Output, Bank of England, October 2012, the Essex Search and Matching Workshop, and the Warwick Macro Work in Progress workshop and the Royal Economic Society Conference 2013 for helpful comments. Sean Milburn of the LFS Research team in the ONS Social Survey Division gave excellent advice on mapping between SICs and SOCs for LFS data.
1. Introduction

The 2008-09 recession saw the UK unemployment rate rise from 5% - the rate that had persisted since 2000 - to around 8% (Figure 1). The unemployment rate has now remained at this relatively high level for nearly four years. Why did unemployment rise, and why has it not fallen? Are there labour market imperfections preventing unemployed workers finding jobs, and through what paths do any such imperfections impact on unemployment?

This paper focuses on the role of mismatch between the distributions of unemployed workers relative to job vacancies. The extent of misallocation in the UK labour market is measured across industry, occupation and region dimensions. An assessment is made as to whether misallocation affects unemployment changes. Mismatch arises when barriers to mobility across labour market segments mean that unemployed workers face costs moving to segments where vacancies are more plentiful, or firms face costs in relocating vacancies. Unemployed workers are effectively constrained to search in the ‘wrong’ segment, so mismatch reduces rates of job finding and job filling, for any given aggregate levels of unemployment and vacancies. Examples of barriers to mobility include industry- or occupation-specific human capital, or relocation costs such as negative housing equity.

Following other recent work on mismatch, the discrepancy between unemployment and vacancies is placed in the context of a search-matching model, which means that two frictions are at work: search and misallocation. At the aggregate level, these two frictions cannot be distinguished, because both are embodied in matching efficiency, the residual of the matching function relationship between job finding and labour market tightness (Furlanetto and Groshenny, 2012; and Figura, 2011). Like other recent work, I use a search-matching framework explicitly modelling mismatch across labour market segments, which allows mismatch and search frictions to be disentangled (Herz and van Rens, 2012; Sahin, Song, Topa and Violante, 2012; Barnichon and Figura, 2011).

Hall (2010) exhorted economists to work on the relationship between unemployment and mismatch: “unemployment is much higher than it would have been absent the dramatic decline in matching efficiency. Research on the severity of unemployment should concentrate on this important fact” (p.9). The response has been good – but most effort has been focussed on the US labour market. To understand the scope for UK monetary policy, it is important to investigate the impact of mismatch on the UK’s unemployment performance during and since the financial crisis. Furthermore, special considerations apply to the UK labour market due to its low turnover: The monthly rate of convergence to flow steady state, which is measured by the sum of job finding and job loss rates, is
only 0.14 in the UK, implying a half-life unemployment duration of 7 months, compared to a typical US convergence rate of 0.61, and a half-life of 1.6 months. Because turnover dynamics matter for the UK, I develop a dynamic model that takes account of the influence of mismatch on unemployment away from its steady state.

In addition to measuring mismatch and capturing its impact on unemployment out of steady state, this paper makes a methodological contribution. First, I show how unemployment movements can be decomposed to distinguish the impact of ‘mismatch’. Any measure of mismatch unemployment can be plugged into the decomposition to estimate the contribution of mismatch to overall unemployment dynamics. I calculate that mismatch contributed around half of the overall rise in UK unemployment during the Great Recession, using the mismatch measure of Sahin, Song, Topa and Violante (2012). These findings are in line with recent findings concerning US unemployment rate: Herz and van Rens (2012) found that mismatch accounts for between 15% and 100% of unemployment fluctuations; Barnichon and Figura (2011) estimate that mismatch raised the rate by 1.5 percentage points in the 2008-09 recession, similar to Sahin, Song, Topa and Violante (2012)’s claim that it explains up to one third of unemployment’s rise.

Then the decomposition method is extended to investigate the paths through which mismatch operates. Surprisingly, the overall contribution of mismatch to unemployment dynamics during the Great Recession substantially exceeds the mismatch contribution working through changes in the job finding rate. This is unexpected, because mismatch is generally thought to operate via the job finding rate: A rise in mismatch will make it harder for unemployed workers to find jobs, so the job finding rate will fall. Empirically, however, a substantial portion of unemployment movements attributable to mismatch cannot be explained by changes in job finding rates due to mismatch. I suggest possible candidate alternative paths through which mismatch could work, including the job loss rate and, in the generalised matching model of Davis, Faberman and Haltiwanger (2012), recruiting intensity.¹

The paper proceeds as follows. After describing measures of mismatch in the UK labour market, I outline a method by which the impact of mismatch can be defined and decomposed. Subsequent sections describe the estimated impacts of mismatch on unemployment and draw conclusions. An Appendix contains details of theory, matching function and data.

¹ In attempting to uncover the paths by which mismatch affects unemployment, this paper has a similar aim to the work of Herz and van Rens (2012), who break mismatch unemployment into four sources by applying a structural model. Wage adjustment costs are found most important, dominating worker and job mobility costs. Results in this paper could reflect dominant wage adjustment costs, since sticky wages could generate a countercyclical job loss rate needed for mismatch working in part via job loss (Michaillat, 2012).
Mismatch

The Beveridge curve

The Beveridge curve expresses the relationship between unemployment and vacancies, both measured as a proportion of the labour force. It is useful to inspect the Beveridge curve as it reflects several factors that influence how well the labour market is working, including how efficiently the searching workers are matched to available vacancies, the rate at which available jobs are filled by firms, and hiring intensity. During the recession, the UK labour market moved south east along a stable Beveridge curve (Figure 2). Subsequently, vacancy creation has been muted. However, unemployment has failed to fall in response to the vacancies that have been created (Figure 3). This leaves open the possibility that there have been adverse changes in mismatch.

Measures of mismatch

Subsequent sections of this paper describe a general method for decomposing unemployment dynamics to identify the role of mismatch and the paths by which mismatch works. To operationalize the method requires an estimate of what the unemployment rate would be in the absence of mismatch. And to extend the method to examine how mismatch works requires an estimate of what the outflow rate would be in the absence of mismatch. The estimates used here are based on two mismatch indices, the first with a long history in the study of misallocation, and the second an extension of this index drawn from Sahin, Song, Topa and Violante (2012).

The idea behind both mismatch indices is to compare vacancies, unemployment and hires in the data with the distributions across sectors that a planner would choose optimally subject to the economy’s frictions and constraints. The planner can costlessly move unemployed workers between sectors, whereas in the real economy there are barriers to worker mobility. In the simple model used here, the barriers correspond to a segmented labour market in which workers can only direct their search towards one sector at a time. Misallocation arises when workers search in the wrong sectors, relative to available vacancies. One mismatch index measures the extent to which the actual allocation of searching workers deviates from the planner’s choice, and the second measures the adverse influence this misallocation has on hiring.

The first index of misallocation $M_{u}$ measures the net proportion of unemployed workers (or vacancies) that would have to be reallocated for the relative distribution of unemployed workers
across sectors to exactly match the desired distribution (corresponding to the distribution of
vacancies):\(^2\)

\[
\mathcal{M}_{Ut} = 0.5 \sum_{i=1}^{I} \left| \frac{u_i}{u_t} - \frac{v_i}{v_t} \right|
\]  

(1)

A rise in \(\mathcal{M}_{Ut}\) indicates greater misallocation: it means that a greater proportion of unemployed
workers are searching in the wrong sector, compared with available vacancy distribution. \(\mathcal{M}_{Ut}\) has
good grounding in the literature: it was used by Jackman and Roper (1987) and is very similar to the
mobility and mismatch indices used by Nickell (1982) and Lilien (1982).

The second mismatch index, \(\mathcal{M}_{Ht}\), is derived explicitly in a search-matching model. This means the
index can take account of matching efficiency (the rate at which searchers match with vacancies),
which is allowed to vary across sectors and over time. So \(\mathcal{M}_{Ht}\) extends \(\mathcal{M}_{Ut}\) by recognising that it is
not only the vacancy distribution that should determine the allocation of searching workers across
sectors, but also the ease with which matching occurs within each sector. Unemployment should be
higher in a sector where matching efficiency is better, because for a given level of vacancies that
sector would generate more hires.

\(\mathcal{M}_{Ht}\) measures the proportion by which actual hires \(h_t^i\) are below the level that would obtain in the
absence of misallocation, \(h_t^{NM}\):

\[
\mathcal{M}_{Ht} = \frac{h_t^{NM} - h_t}{h_t^{NM}} = 1 - \sum_{i=1}^{I} \left( \frac{\phi_i}{\bar{\phi}} \right) \left( \frac{v_i}{v_t} \right)^{1-\alpha} \left( \frac{u_i}{u_t} \right)^{\alpha}
\]  

(2)

where \(\phi_i\) is matching efficiency in sector \(i\) and \(\bar{\phi}\) is an average measure of matching efficiency (see
Appendix 1 for details).

Empirical measures of misallocation \(\mathcal{M}_{Ut}\) and \(\mathcal{M}_{Ht}\) across UK industries are shown in Figure 4.
Figures 5 and 6 show misallocation across occupations and regions, respectively. These empirical
measures are based on data from the quarterly Labour Force Survey, Claimant count, Jobcentre Plus
and Vacancy Survey. Details are provided in Appendix 2.

\(^2\) Here and in what follows, unemployment, vacancies and hires are expressed as proportions of the relevant
labour force.
Not surprisingly, taking the model to the data reveals a misallocation index $\mathcal{M}_{hi}$ always greater than zero, consistent with fewer actual hires than in the absence of misallocation ($h_i < h_i^{NM}$). This hires deficit reflects the fact that unemployed workers are searching in the wrong sectors in terms of vacancies ($\mathcal{M}_{hi} > 0$).

The cyclical behaviour of the various mismatch indices differs. Misallocation of unemployed workers across industries, relative to vacancies, rose in the 2008-09 financial crisis, and hires fell as a result. Hires have recovered since, even though the distribution of unemployment relative to vacancies took a considerable time to return to normal.

Misallocation across occupations appears to have risen during 2008 and, although there was some recovery and stability through 2010, misallocation across occupations has since risen further.\(^3\) According to the data, then, adjustment at industry level has been easier than by occupation. The overall level of the regional mismatch measure is slightly lower than comparable figures at occupation and industry levels. A marked decline in the discrepancy between region unemployment and vacancy shares started in 2006 and continued through the 2008-09 recession. Regional mismatch also fell leading up to, and troughed during, the 1990s recession, according to the Claimant Count-based index. For both occupation and region, unlike industry, changes in misallocation have had relatively low impact on hires. Comparison of (1) and (2) suggests that one reason for this contrast between and is that although unemployment rose relative to vacancies, the occupations and regions that saw the largest rises were those where matching efficiency is highest.\(^4\)

**Mismatch, job finding and unemployment**

A key message of this paper will be that looking at mismatch indices in isolation can give a misleading idea of the impact of misallocation on labour market outcomes. Subsequent sections will demonstrate that even after dissipation of misallocation as measured by the discrepancy between unemployment and vacancies, and even after the hiring rate returns to a normal level, a mismatch shock has a persistent impact on unemployment.

\(^3\) There is little difference between Claimant Count unemployment by usual and sought occupation. If these data are credible, it would suggest that benefit claimants do not direct their search to occupations in relation to job openings: intended occupational mobility does nothing to reduce mismatch. Figure 5’s picture of UK occupational mismatch is similar to that in Sahin, Song, Topa and Violante’s (2010) work for the UK, although they did not record the mismatch increase from 2011: Their occupation-based sample ended in mid-2010 and used Jobcentre Plus unfilled live vacancies and Claimant Count unemployment measured at 2- or 3-digit levels.

\(^4\) Matching function estimates indicate that matching efficiency is highest in southern and eastern regions, including London, and among higher-skilled occupations. Data confirm that London and the South East experienced the largest rises in unemployment and that London had a relatively small rise in vacancies.
Fundamentally, the impact of mismatch on unemployment and its dynamics arises because mismatch reduces the job finding rate. $H_{t}$ enables the impact of mismatch on job finding rates to be calculated. The actual job finding rate, including any mismatch effect, is defined as

$$
  f_{t} = \frac{h_{t}}{u_{t}}
$$

(3)

The job finding rate in the absence of mismatch is

$$
  f_{t}^{NM} = f_{t} \left( \frac{1}{1 - H_{t}} \right) \left( \frac{u_{t}}{u_{t}^{NM}} \right)^{\alpha}
$$

(4)

$f_{t}^{NM}$ is the job finding rate that would arise if a planner were able to allocate unemployed searchers in accordance with the exogenous distribution of vacancies and sector-specific matching efficiencies (see the Appendix for derivations).

Labour market developments are driven by the job finding rate and unemployment, because vacancies and the job loss rate are assumed exogenous, as in the majority of modern search-matching models. Note that this relates to the term $1/(1 - H_{t})$ in (4), which Sahin, Song, Topa and Violante (2012) term the ‘direct effect’ of misallocation. Correspondingly, the actual unemployment rate is always higher than the no-mismatch unemployment rate ($u_{t} > u_{t}^{NM}$). Because the job finding rate is less than unity, any increase in misallocation that raises unemployment will have a persistent impact. The extra unemployment will not be instantaneously eliminated even when the job finding rate rises back to normal levels after $H_{t}$ falls. Sahin, Song, Topa and Violante (2012) term this a ‘feedback effect’. The number of hires should at that point be higher than its pre-misallocation-shock level.

Using the estimate of $H_{t}$ derived from data on hires, vacancies and unemployment, estimates of the no-mismatch unemployment and job finding rates can be simultaneously and recursively obtained. The dynamic path of the no-mismatch unemployment rate is described by the usual recursive law of motion for unemployment (see equation (7) below), but based on flow and unemployment rates in the absence of mismatch:

$$
  u_{t}^{NM} = s_{t} + \left( 1 - s_{t} - f_{t}^{NM} \right) u_{t}^{NM}
$$

(5)
The initial conditions are specified as $u_0^* = \bar{u}_0^*$ and $f_0^* = f_0/\left(1 - \mathcal{M}_0\right)$, implying that at date 0 unemployment is at its flow-steady state level and that the impact of mismatch on the job finding rate is limited to its direct effect (there is no feedback effect at date 0). Due to persistence in the process driving aggregate unemployment, it takes time for the impact of the initial condition to fade away. Graphs and estimates therefore omit the first four quarters after date 0, since these will be misleading as to the true behaviour of unemployment and flow rates.

The next sections show how mismatch and its relationship with unemployment can be measured, before turning to a theoretical model and empirical estimates of the impact of mismatch in the UK.

**The impact of mismatch on the level and dynamics of unemployment**

In this section I describe a basic accounting model of unemployment dynamics and how it can be expanded to look at the role of mismatch. The model is couched in terms of only two states, implying that workers can be either employed or unemployed and the labour force has constant size. Because observed unemployment also reflects nonparticipation dynamics, empirical implementation uses measures of total unemployment inflows and outflows that incorporate flows via nonparticipation in addition to direct flows between unemployment and employment (see Smith, 2011, and Petrongolo and Pissarides, 2008).

**Unemployment, labour market flows, and mismatch**

The analysis starts with the law of motion for unemployment expressed in discrete time, which simply states that current unemployment differs from unemployment last period by the addition of new inflows and the deduction of outflows during the period:

$$\Delta U_{t+1} = s_t E_t - f_t U_t$$

(6)

where $\Delta U_{t+1}$ is the change in unemployment between the start of period $t$ and the start of period $t+1$. $f_t$ is the probability of transiting out unemployment during $t$, which will also be referred to here as the unemployment outflow or job finding rate. Empirically, $f_t$ is calculated as the number of people who were unemployed at the beginning of period $t$ and are observed in employment at the start of $t+1$, divided by the stock of unemployment at the start of period $t$. $s_t$ is the inflow probability (also referred to here as the inflow or job loss rate), reflecting the probability of becoming unemployed during $t$. Multiplying this inflow probability by the stock of employment gives the volume of gross inflows $EU_t$. 
Dividing (6) by the labour force expresses the law of motion in terms of the unemployment rate $u_t$:

$$\Delta u_{t+1} = s_i (1 - u_t) - f_t u_t$$

(7)

Rearranging (7) it is possible to define $\overline{u}_t$, the rate that unemployment will converge towards if inflow and outflow probabilities do not alter from their current values:

$$\overline{u}_t = \frac{s_i}{f_i + s_i}$$

(8)

$\overline{u}_t$ is known as the flow steady state unemployment rate. $\overline{u}_t$ varies over time, always reflecting current labour market flow rates. A rearrangement of (7) clarifies the dynamics of the unemployment rate around its flow steady state value:

$$u_{t+1} = (f_i + s_i) \overline{u}_t + \left[1 - (f_i + s_i)\right] u_t$$

(9)

The rate of convergence to the flow steady state is $\left( f_i + s_i \right)$. The higher are flow transition rates (precisely, the closer their sum is to unity), the lower the deviation of the unemployment rate at the start of period $t+1$ from its flow steady state value. If flow rates are low, then past (shocks to) flow rates will impact on current unemployment. In (9), the cumulative impact of past flow rates is captured in last period’s unemployment rate $u_{t-1}$.

How does this help us think about the effect of mismatch? Mismatch captures the idea that it will be harder for the unemployed to get jobs if their skills and characteristics are less well suited to the requirements of available job openings. Greater mismatch will reduce the unemployment outflow rate $f_t$. Equations (8) and (9) indicate the two routes through which this direct effect of mismatch on the outflow rate will act. Greater mismatch directly raises the steady state unemployment rate $\overline{u}_t = s_i / (f_i + s_i)$. More mismatch also increases unemployment persistence $\left[1 - (f_i + s_i)\right]$, so greater mismatch mutes the initial impact of the outflow rate shock but lengthens the time over which the adverse impact is felt.

If we have an estimate of the counterfactual no-mismatch outflow rate, $f^{NM}_t$, then these misallocation impact can be estimated, using $f^M_t = f_t - f^{NM}_t < 0$. A worse allocation makes $f^M_t$ more negative: the observed job finding rate $f_t$ falls further below the no-misallocation rate $f^{NM}_t$. 

9
Decomposing unemployment dynamics

The next step involves formally estimating the role of mismatch on unemployment and its dynamics. The methods used are able to calculate the overall impact of mismatch and the relative importance of its effects via outflow and inflow rates.

The method of decomposing the impact of mismatch on unemployment dynamics extends recent work by Smith (2011) and Elsby, Hobijn and Sahin (forthcoming) who developed models of non-steady state unemployment dynamics based on (9). Smith models the dynamics of the unemployment rate itself, whereas Elsby, Hobijn and Sahin model log unemployment dynamics. Results from both variants are very similar. In what follows, I develop the model of log unemployment dynamics to incorporate the influence of mismatch.

Building on Elsby, Hobijn and Sahin (forthcoming), changes in log unemployment can be expressed

\[
\Delta \ln u_{t+1} \approx \rho_i \Delta \ln \bar{u}_{t+1} + \left( \rho_1 / \rho_{t-1} - \rho_i \right) \Delta \ln u_t
\]  

(10)

where \( \rho_i = f_i + s_i \) is the sum of unemployment inflow and outflow transition probabilities. The first term on the right hand side of (10) embodies current shocks to the flow steady state unemployment rate \( \bar{u}_i \). These are contemporaneous shocks affecting flow transition rates \( f_i \) and \( s_i \). The history of previous inflow and outflow shocks led to changes in past steady state unemployment rates and have a lagged effect on current unemployment dynamics through the final term in (10). Current and previous-period flow rate shocks also alter the relative size of the innovation coefficient \( \rho_i \) and recursive coefficient \( \left( \rho_1 / \rho_{t-1} - \rho_i \right) \). Comparing (9) and (10), the rate of convergence of changes in log unemployment to changes in flow steady state unemployment is identical to the convergence rate for the respective unemployment rates. The recursive coefficient differs: intuitively, the dynamic version \( \left( \rho_1 / \rho_{t-1} - \rho_i \right) \) adjusts for changes in flow transition rates over time.

A model of flow steady state unemployment dynamics would focus only on \( \Delta \ln \bar{u}_i \).

The impact of mismatch on unemployment dynamics

It is useful to investigate the impact of mismatch on flow steady state unemployment dynamics, since equation (10) shows that unemployment dynamics out of steady state can be expressed as a recursive weighted sum of flow steady state dynamics.
To decompose the impact of mismatch requires an estimate of the counterfactual steady state unemployment rate in the absence of mismatch, $\bar{u}_i^{NM}$. Given this, the overall impact of mismatch on unemployment dynamics can be obtained simply.

The steady state unemployment rate $\bar{u}_i$ can be decomposed into the rate that would obtain if there were no mismatch, $\bar{u}_i^{NM}$, and a part reflecting mismatch, $\bar{u}_i^M = \bar{u}_i - \bar{u}_i^{NM}$:

$$\bar{u}_i = \bar{u}_i^M + \bar{u}_i^{NM} \quad (11)$$

Taking log differences demonstrates that the log change in the flow steady state unemployment rate is a share-weighted sum of the log changes of the two terms in (11):

$$\ln 1 \ln \ln \Delta \bar{u}_i^M + v_i \Delta \bar{u}_i^{NM} \quad (12)$$

where $v_i = \bar{u}_i^{NM} / \bar{u}_i$. The two terms in (12) are the contribution of mismatch to flow steady state log unemployment dynamics, $\bar{C}_i^M$, and the contribution of non-mismatch shocks, $\bar{C}_i^{NM}$:

$$\bar{C}_i^M = (1 - v_i) \Delta \ln \bar{u}_i^M \quad (13)$$

$$\bar{C}_i^{NM} = v_i \Delta \ln \bar{u}_i^{NM} \quad (14)$$

These contributions together describe the movement of the flow steady state unemployment rate.

The overall influence of mismatch on changes in flow steady state unemployment can be estimated by the covariance contribution of mismatch shocks to the variance of flow steady state unemployment, in the spirit of Fujita and Ramey’s (2009) variance decomposition:

$$\bar{\beta}^M = \frac{\text{cov}(\bar{C}_i^M, \Delta \ln \bar{u}_i)}{\text{var}(\Delta \ln \bar{u}_i)} \quad (15)$$

A similar statistic can be defined for non-mismatch shocks. Together, mismatch and non-mismatch shocks account for all variation in steady state unemployment, subject to approximation error:

$$\bar{\beta}^M + \bar{\beta}^{NM} \approx 1$$. Empirical measures of these betas are shown in Table 2, discussed below. An alternative picture of the mismatch contribution during the financial crisis could be obtained by plotting the cumulative mismatch contribution $\bar{C}_i^M$ from the start of the crisis (see Figures 13 to 15).

Contributions to non-steady state dynamics emerge from (10), noting that $\Delta \ln \bar{u}_i = \bar{C}_i^M + \bar{C}_i^{NM}$. So
\[ C_{t+1}^M = \rho_t C_{t+1}^M + \left( \rho_t / \rho_{t-1} - \rho_t \right) C_t^M \]  

where the initial condition is defined as \( C_0^M = \rho_0 C_0^M \). An analogous expression defines \( C_{t+1}^{NM} \).

Permanently greater mismatch makes it more difficult for policymakers to reduce unemployment, but it will also tend to reduce unemployment volatility. This arises because a permanent increase in mismatch raises the impact on unemployment dynamics of past shocks to flow transition rates, but reduces the impact of current shocks.

**The impact of mismatch via outflow and inflow rates**

Digging deeper can uncover the paths by which misallocation affects unemployment. The impact of mismatch via inflow and outflow rates can be separately distinguished. Changes in the steady state unemployment rate can be decomposed into four parts:

\[
\ln f_{it} = \ln f_{it}^M + \ln f_{it}^{NM}
\]

Consider first the influence of mismatch on unemployment working via the outflow rate. Given an estimate of \( f_{it}^{NM} \), the outflow rate in the absence of mismatch, the overall outflow rate can be decomposed

\[
f_{it} = f_{it}^M + f_{it}^{NM}
\]

\( f_{it}^M = \left( f_{it} - f_{it}^{NM} \right) < 0 \) is the mismatch component of the overall outflow rate \( f_{it} \), and is negative because misallocation reduces the outflow rate relative to the no-misallocation case.

A decomposition of unemployment dynamics can reveal the degree to which misallocation influences unemployment through the outflow rate. As shown by (10) above, unemployment rate dynamics can be expressed as a recursive weighted sum of changes in the flow steady state unemployment rate. The flow steady state unemployment rate itself can be decomposed to separate the effects of misallocation on the job finding rate:

\[
\ln f_{it} = \ln f_{it}^M + \ln f_{it}^{NM}
\]

Then, using the result of Elsby, Michaels and Solon (2009) that changes in flow steady state unemployment can be expressed in terms of changes in current flow transition rates,

\[
\Delta \ln s_t = \left( \frac{s_t}{f_t + s_t} \right) \left( \Delta \ln s_t - \Delta \ln f_t \right) = \left( \frac{s_t}{f_t + s_t} \right) \left\{ \Delta \ln s_t - \Delta \ln \left( f_{it}^M + f_{it}^{NM} \right) \right\}
\]
To estimate, rearrange the final outflow rate term in (20):

\[
\Delta \ln \left( \left[ f_i - f_i^{NM} \right] + f_i^{NM} \right) \approx (1 - \varphi_i) \left[ (1 - \eta_i) \Delta \ln f_i + \eta_i \Delta \ln f_i^{NM} \right] + \varphi_i \Delta \ln f_i^{NM}
\]

(21)

where \( \varphi_i = f_i^{NM} / f_i \) and \( \eta_i = - f_i^{NM} / (f_i - f_i^{NM}) \).

The contributions to flow steady state unemployment movements of mismatch and non-mismatch shocks working directly via the outflow rate are, respectively,

\[
\bar{C}_{i}^{TM} = - (1 - \bar{u}_{i-1}) (1 - \varphi_i) \left[ (1 - \eta_i) \Delta \ln f_i + \eta_i \Delta \ln f_i^{NM} \right]
\]

(22)

\[
\bar{C}_{i}^{TNM} = - (1 - \bar{u}_{i-1}) \varphi_i \Delta \ln f_i^{NM}
\]

(23)

So far it has been explained how \( \bar{C}_{i}^{TM} \), \( \bar{C}_{i}^{TNM} \), \( \bar{C}_{i}^{s} \), \( \bar{C}_{i}^{JM} \) and \( \bar{C}_{i}^{JNM} \) can be directly estimated. The remaining issue is how the overall inflow rate contribution \( \bar{C}_{i}^{s} \) can be split into misallocation and non-misallocation components, \( \bar{C}_{i}^{sM} \) and \( \bar{C}_{i}^{sNM} \). To see this, note that the misallocation component is given by

\[
\bar{C}_{i}^{sM} = \bar{C}_{i}^{s} - \bar{C}_{i}^{JM}
\]

(24)

where the right hand side is simply the difference between equations (13) and (22). Then

\[
\bar{C}_{i}^{sNM} = \bar{C}_{i}^{s} - \bar{C}_{i}^{sM}
\]

(25)

where \( \bar{C}_{i}^{s} = (1 - \bar{u}_{i-1}) \Delta \ln s_i \), using Elsby, Michaels and Solon’s (2009) result shown as the left hand side of (20). The non-misallocation component of the inflow rate impact on flow steady state unemployment could also be calculated as the difference between the overall non-misallocation contribution (14) and the non-misallocation outflow rate contribution (23); since the decompositions are based on identities, the results are identical.

**Job loss cyclicity and mismatch**

Greater mismatch could also have an effect on unemployment if it alters the inflow rate \( s_i \).

Mismatch lowers the hiring rate and reduces employment. Mismatch will affect the inflow rate

\[ s_i = EU_i / E_i \]

if gross flows out of employment to unemployment \( EU_i \) do not vary proportionately with this mismatch-induced employment change. Possible reasons for less-than-proportionate variation could include factors leading to countercyclical separations, including for example wage
rigidity. Indeed, evidence tends to suggest a countercyclical separation rate, and procyclical employment (for example, Davis, Faberman and Haltiwanger, 2006). A rise in mismatch would then raise the inflow rate, which would in turn raise the steady state unemployment rate. Algebraically, 
\[
\frac{\partial u}{\partial f} \frac{\partial s}{\partial f} = \frac{(s - f)}{(s + f)^3} < 0 \quad \text{since} \quad f \gg s. 
\]
An increase in the inflow rate due to mismatch would reduce unemployment persistence.

The notions that job loss contributes substantially to unemployment dynamics, and furthermore that mismatch might influence this contribution, are controversial. As Shigeru and Ramey (2012) note, “there is little consensus as to the proper treatment of the separation margin” in the Mortensen-Pissarides (MP) search-matching model. There has been a tendency to assume an exogenous and constant job loss (or separation) rate even though, with a constant separation rate, the MP model underpredicts unemployment volatility (Shimer, 2005).

How could mismatch directly influence the job loss rate, so that \( C_t^{IM} \neq 0 \)? To see what is implied, consider the situation of the UK as it emerged from recession, with mismatch declining (when it is measured across industries). How could a reduction in mismatch increase the job loss rate, relative to the job loss rate in the absence of mismatch? Any increase in the job loss rate (relative to the counterfactual) would mute the decline in unemployment as the economy recovers from recession. The unemployment rate would fail to fall as fast as warranted by the recovery in the job finding rate.

To understand how this could come about, note that the job loss rate is the ratio of the gross job loss flow to the stock of employment. The denominator – employment – rises as mismatch declines, since a reduction in mismatch entails more hires. The issue is then whether the volume of job loss will rise at a slower rate than employment. Dividing job loss into quits (voluntary) and redundancies (involuntary) gives a clue as to how this could arise. Voluntary quits will rise with employment (quits are procyclical). However, involuntary job loss flows (redundancies) tend to be countercyclical (see also Carillo-Tudela and Visschers, 2013). Thus the proportionate rise in overall job loss might be lower than the proportionate increase in employment – entailing a rise in the job loss rate – as mismatch falls. Thus mismatch would mute the countercyclicality of the job loss rate, with the result that, as the economy heads out of recession, the unemployment rate fails to fall as fast as the rising job finding rate warrants.

It is worth clarifying that mismatch does not work directly on job loss flows, but it does work directly on the job loss rate. This direct effect arises simply because of the effect of mismatch on employment, working via the impact of mismatch on hiring.
Results

The impact of mismatch on the outflow rate

Figures 10 to 12 graph the counterfactual outflow rate in the absence of mismatch, given by equation (4), and the actual outflow rate, \( f_t \). The no-mismatch job finding rate, \( f_{NM}^t \), should capture all non-mismatch shocks. The distance between the two series measures the impact of mismatch on the outflow rate, which is negative.

The increase in mismatch between 2008 and 2010 discussed above is apparent in some increase in the distance between the actual and no-mismatch job finding rates, for mismatch measured across all dimensions. However, the downward trend in the job finding rate dominates the overall picture. So the impact on the job finding rate is more difficult to discern than the impact on the unemployment rate itself, and certainly appears to dissipate faster. Since 2010, the distance between actual and no-mismatch outflow rates has shrunk, as mismatch has fallen back to its ‘normal’ level.

The impact of mismatch on the steady state unemployment rate

To see how mismatch has changed the steady state unemployment rate, note that changes in the log flow steady state unemployment rate can be simply decomposed into a part attributable to changes in mismatch and a part due to non-mismatch shocks. These shocks are captured, respectively, by the log change in the difference between flow steady state and no-mismatch flow steady state rates, and by the change in the log flow steady state no-mismatch unemployment rate.

Figures 13 to 15 plot these contributions to log flow steady state unemployment dynamics. Mismatch shocks explain around half of the rise in the steady state unemployment rate during the 2008-09 recession. Post-recession, there has been a slight tendency for mismatch shocks (reductions) to reduce flow steady state unemployment (so the mismatch contribution declines). Increases in the flow steady state unemployment rate post-recession have tended to reflect the contribution of other, non-mismatch, shocks.

A variance decomposition clarifies that mismatch shocks played an unusually large part in unemployment movements during the recession, as measured by the flow steady state rate (see Table 2). The contribution of mismatch across all dimensions rose substantially. For example, industry mismatch accounted for 64% of unemployment movements in the recession, compared to around 50% normally. The usual contribution of mismatch measured across broad occupations and regions is lower, at around 33%-35%. The rise in occupational mismatch accounted for nearly 60% of
unemployment changes in the recession. It might have been expected that regional mismatch would have played a large role too, given that the reduction in house prices and increased difficulty in obtaining mortgages would have locked people to their existing accommodation. However, changes in regional mismatch appear to account for a relatively low proportion of unemployment dynamics.

Post-recession, the effect of occupation and regional mismatch relative to other influences has declined back to a typical level, although industry mismatch continues to play a larger-than-normal role. Perhaps surprisingly, mismatch does appear to play a substantial part in changes in flow steady state unemployment in normal times. These findings echo those of Herz and van Rens (2012), who concluded – on the basis of US data across industries and across states – that “structural” (mismatch) and actual unemployment are equally cyclical.

Findings concerning the flow steady state unemployment rate are very important for understanding UK unemployment and its dynamics. Although this paper argues that a full picture requires a dynamic model, it is clear that that model depends on current shocks that drive the flow steady state rate – and, furthermore, the dynamics of actual unemployment depend on past flow steady state rates (summarising past shocks).

Mismatch paths
The decomposition can be elaborated to examine the routes through which mismatch works. Estimating equations (22) through (25) gives contributions to steady state unemployment dynamics of changes in inflow and outflow rates involving mismatch and non-mismatch shocks. These contributions are additive, so the variance of changes in unemployment can be decomposed to investigate their role in unemployment dynamics. The results, shown in Table 3 for mismatch across industries, are surprising. Mismatch does not operate only via the job finding rate.

As discussed above, one other possible candidate mismatch paths is the job loss rate. Consider the rise in industrial mismatch in the 2008-09 recession. This will directly reduce overall hires and employment relative to the no-mismatch case. If employment outflows do not fall proportionately, the separation rate will be higher than in the no-mismatch case. The consequently higher unemployment rate would represent a mismatch effect working via the job loss rate.

A further candidate is recruiting intensity (Davis, Faberman and Haltiwanger, 2012). The matching model can be modified to allow flexibility in the effort firms make to fill vacancies. For any given level of vacancies, a reduction in recruiting intensity would reduce job filling and hiring rates. Mismatch could cause fluctuations in recruiting intensity. For example, measured sectoral mismatch could reflect barriers to mobility of vacancies. A reduction in vacancy mobility would reduce firms’
incentives to recruit, because in the segment in which vacancies are currently located, match quality would on average be lower. Recruiting intensity could also be affected by mismatch if the barriers affect worker mobility.

**Impact of mismatch on the actual unemployment rate**

The impact of mismatch on the actual unemployment rate will reflect its impact on the flow steady state rate, modified by the level of and changes in the innovation and recursive coefficients. The gap between actual and no-mismatch actual unemployment rates was around 1.2 percentage points in the early 2000s, rising to 1.7 percentage points just prior to the 2008-09 recession. During the recession this gap rose to around 2.5 percentage points, and after 2009 the gap increased further. The large divergence between actual and no-mismatch unemployment only really began in 2009. Some might anticipate that mismatch shocks would have most impact *during* the recession. One reason to change this expectation might be inspection of the Beveridge curve in Figure 2. During the recession, the fall in demand was accompanied by lower vacancy creation and a move south-east along a stable Beveridge curve. It was only after the recession ended that there is any sign of a possible outward and upward shift in the Beveridge curve consistent with increased mismatch.

An additional factor behind the delayed response of actual unemployment to mismatch is the sclerotic nature of the UK labour market. Relatively low turnover rates mean that there is a ‘lagged’ response of actual unemployment to changes in mismatch: the quarterly recursive coefficient averages around 0.7. The impact of mismatch on innovation and recursive coefficients is plotted in Figure 16. As industry mismatch rose, and job finding fell, in the recession, the innovation and recursive coefficients both fell. The continued fall in innovation coefficient reflects the lingering impact of mismatch. Increased mismatch reduces the innovation coefficient, meaning that actual unemployment will take longer to respond to flow rate shocks. Following a temporary fall, as discussed above, there is a corresponding rise in the recursive coefficient implying a larger impact of past shocks.

**Conclusion**

This paper has investigated whether the behaviour of UK unemployment is linked to misallocation. In particular, did the rise in unemployment during the financial crisis of the late 2000s result in a pool of unemployed workers whose characteristics – in terms of industry, occupation or location – do not match requirements of available job openings?
The paper tied together dynamic decompositions of actual unemployment with measures of misallocation between unemployment and vacancies. Accounting exercises were performed that led to estimates of the extent to which actual and steady state UK unemployment were raised due to mismatch between unemployment and vacancies across industries, occupations and regions, and estimates of the effects of mismatch on the dynamic path towards the steady state.

Results indicate that, overall, misallocation contributed around one half of the rise in UK unemployment during the financial crisis. Digging deeper led to the surprising result that misallocation appears to work through channels other than simply job finding. Possible alternative paths through which misallocation could work include the job loss rate and recruiting intensity.

The profiles of mismatch across industries, occupation and region are not identical. Industry mismatch tends to be countercyclical: Industry mismatch rose rapidly in the recession, but recovered fairly quickly – following an inverted V shape. Regional mismatch paints a contrasting picture: Evidence from two recessions suggests that unemployment and vacancies alter in downturns so that their regional distributions become more, rather than less, similar. But like industry mismatch, regional mismatch returns to ‘normal’ levels quickly after recessions. Mismatch measured across occupations shows variation that is not so readily related to the overall state of the economy. In particular, occupational mismatch is estimated to have risen to a peak in 2009, failed to fall back fully afterwards, and then to have begun rising again. Unemployment movements, of course, reflect the complex net effect of misallocation across all dimensions.

References


Herz, Benedikt and Thijs van Rens (2012), “Structural unemployment”, University of Warwick mimeo.


Table 1: Matching function estimates of the vacancy share, $\alpha$

<table>
<thead>
<tr>
<th>Matching function</th>
<th>$\alpha$</th>
<th>s.e.</th>
<th>$R^2$</th>
<th>Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Industry total hires</td>
<td>0.615*** (0.0264)</td>
<td>0.675</td>
<td>810</td>
<td></td>
</tr>
<tr>
<td>(2) Occupation total hires</td>
<td>0.435*** (0.0257)</td>
<td>0.862</td>
<td>369</td>
<td></td>
</tr>
<tr>
<td>(3) Region total hires</td>
<td>0.541*** (0.0260)</td>
<td>0.881</td>
<td>638</td>
<td></td>
</tr>
</tbody>
</table>

Note: Sample periods are 2001q3-2012q3 (18 industries), 2002q3-2012q3 (9 occupations), 1997q3-2012q3 (11 regions). All regressions include sector fixed effects, a quadratic time trend and seasonal dummies. Standard errors in parentheses. *** indicates significance at the 1% level.

Table 2: Relative effects of mismatch and other shocks on changes in the flow steady state unemployment rate

<table>
<thead>
<tr>
<th></th>
<th>Mismatch</th>
<th>Non-mismatch</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Industry</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Recession</td>
<td>0.64</td>
<td>0.36</td>
</tr>
<tr>
<td>Post-recession</td>
<td>0.47</td>
<td>0.53</td>
</tr>
<tr>
<td>Pre-recession</td>
<td>0.55</td>
<td>0.45</td>
</tr>
<tr>
<td>Full sample</td>
<td>0.52</td>
<td>0.48</td>
</tr>
<tr>
<td><strong>Occupation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Recession</td>
<td>0.59</td>
<td>0.41</td>
</tr>
<tr>
<td>Post-recession</td>
<td>0.24</td>
<td>0.76</td>
</tr>
<tr>
<td>Pre-recession</td>
<td>0.36</td>
<td>0.66</td>
</tr>
<tr>
<td>Full sample</td>
<td>0.33</td>
<td>0.69</td>
</tr>
<tr>
<td><strong>Region</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Recession</td>
<td>0.44</td>
<td>0.55</td>
</tr>
<tr>
<td>Post-recession</td>
<td>0.31</td>
<td>0.69</td>
</tr>
<tr>
<td>Pre-recession</td>
<td>0.38</td>
<td>0.61</td>
</tr>
<tr>
<td>Full sample</td>
<td>0.35</td>
<td>0.65</td>
</tr>
</tbody>
</table>

Note: Estimates are ‘betas’ from a variance decomposition of the steady state unemployment rate, and represent the relative contribution of non-mismatch shocks (embodied in changes in the no-mismatch steady state unemployment rate) and mismatch shocks (embodied in changes in the difference between the steady state rate and the no-mismatch steady state rate). Columns might not sum to unity due to rounding. Due to lack of data, 2000q4-2002q2 is excluded from the occupational sample and 2001q3-2002q2 is excluded from the regional sample.
Table 3: Mismatch paths: Industry mismatch

<table>
<thead>
<tr>
<th></th>
<th>Mismatch</th>
<th></th>
<th>Non-mismatch</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>f</td>
<td>unexplained</td>
<td>f</td>
</tr>
<tr>
<td>Pre-recession</td>
<td>2001q3-2008q1</td>
<td>6%</td>
<td>39%</td>
<td>38%</td>
</tr>
<tr>
<td>Recession</td>
<td>2008q2-2009q3</td>
<td>11%</td>
<td>44%</td>
<td>33%</td>
</tr>
<tr>
<td>Post-recession</td>
<td>2009q4-2011q4</td>
<td>12%</td>
<td>35%</td>
<td>8%</td>
</tr>
<tr>
<td>Full sample</td>
<td>2001q3-2011q4</td>
<td>8%</td>
<td>38%</td>
<td>29%</td>
</tr>
</tbody>
</table>
Figures

**Figure 1: UK unemployment rate**

Unemployment as proportion of labour force (%)

- **LFS micro data SA**
- **MGSX**

Note: Age 16+. SA using X12. Source: Quarterly LFS, 1992q2-2012q3; ONS LFS MGSX.
Figure 2. Beveridge Curve, 2001-2012

Figure 3. Beveridge Curve, 2008-2012

Sources: Author’s calculations using ONS Vacancy Survey and LFS.
Figure 4: Mismatch across industries

$M_{UV}$ and $M_h$ misallocation indices: industry

Sources: Quarterly LFS and ONS Vacancy Survey, 2001q2-2012q3.

Figure 5: Mismatch across occupations

$M_{UV}$ and $M_h$ misallocation indices: occupation

Sources: Quarterly LFS and NOMIS, 2002q3-2012q3.
**Figure 6: Mismatch across regions**

![Graph showing M_H and M_UV misallocation indices](image)

Sources: Quarterly LFS [1997q2-2012q3], NOMIS Claimant Count and Notified Jobcentre Vacancies, 1985q3-2012q4 excl 2001q3-2002q1.

**Figure 7: Impact of industrial mismatch on aggregate unemployment**

![Graph showing unemployment rates](image)

Source: Quarterly LFS and Vacancy Survey.
Figure 8: Impact of occupational mismatch on aggregate unemployment

Source: Quarterly LFS and Jobcentre Plus vacancies.

Figure 9: Impact of regional mismatch on aggregate unemployment

Source: Quarterly LFS and Jobcentre Plus vacancies.
**Figure 10:** Impact of industrial mismatch on the job finding rate

Quarterly unemployment outflow rates

Source: Quarterly LFS and Jobcentre Plus vacancies.

**Figure 11:** Impact of occupational mismatch on the job finding rate

Quarterly unemployment outflow rates

Source: Quarterly LFS and Jobcentre Plus vacancies.
**Figure 12:** Impact of regional mismatch on the job finding rate

![Figure 12](image1.png)

Source: Quarterly LFS and Jobcentre Plus vacancies.

**Figure 13:** Contributions of industry mismatch and other shocks to steady state unemployment dynamics

![Figure 13](image2.png)

Source: Quarterly LFS and Jobcentre Plus vacancies.

*Note: The graph plots cumulative log changes in components of the steady state unemployment rate.*
**Figure 14**: Contributions of occupational mismatch and other shocks to steady state unemployment dynamics

![Graph showing cumulative log changes in components of the steady state unemployment rate.](image)

Source: Quarterly LFS and Jobcentre Plus vacancies.

*Note: The graph plots cumulative log changes in components of the steady state unemployment rate.*

**Figure 15**: Contributions of regional mismatch and other shocks to steady state unemployment dynamics

![Graph showing cumulative log changes in components of the steady state unemployment rate.](image)

Source: Quarterly LFS and Jobcentre Plus vacancies.

*Note: The graph plots cumulative log changes in components of the steady state unemployment rate.*
Figure 16: Difference between actual data and no-industry-mismatch counterfactual, as a proportion of actual data, in the impacts of current and past flow rate shocks on current unemployment.
Appendix 1: Derivation of mismatch index $\mathcal{M}_{Ht}$

The mismatch index $\mathcal{M}_{Ht}$ is derived from a directed search model of the labour market in which there are $I$ distinct sectors, indexed by $i$. Frictions affect each of these labour markets. Vacancies $v_{it}$ in market $i$ at time $t$ are filled (only) by unemployed workers $u_{it}$ searching in that market. The simplest model takes vacancy creation to be exogenous.

Hires $h_{it}$ are determined by a matching function embodying frictions:

$$h_{it} = \Phi_i \phi_i m(u_{it}, v_{it})$$

where $m$ is increasing and strictly concave in both arguments and homogenous of degree one in $(u_{it}, v_{it})$. $\phi_i$ measures the sector-specific component of matching efficiency, and $\Phi_i$ captures developments in matching efficiency common to all sectors.

Further assumptions are that firms face a sector-specific vacancy posting cost that determines $v_{it}$, matches are exogenously destroyed at rate $\Delta_i$, and existing workers produce $Z_i$ units of output, where $\Delta_i$ and $Z_i$ are aggregate shocks following a joint Markov process. In the simplest model, the vacancy posting cost is exogenous. Sector-specific matching efficiencies and vacancy posting costs reflect both aggregate shocks and their own sector-specific innovations.\(^5\)

At the beginning of each period, the distributions across sectors of employment (remaining existing matches) and vacancies is taken as given. Aggregate shocks and the distributions of matching efficiencies and vacancy costs across sectors are then realised. Because the economy has measure one of agents, who can be either employed or unemployed, the volume of unemployment is given. But the distribution of unemployment across sectors is only determined after shocks are realised, once the unemployed workers decide to direct their search towards a particular sector. After this allocation of unemployment to sectors, the matching process takes place. Existing employees and new hires then engage in production (with the productivity of new hires a fixed proportion below that of existing employees). Exogenous aggregate match destruction and voluntary quitting at sector-specific rates then occur, and finally next period’s vacancies are created.

The idea behind the mismatch index is to compare vacancies, unemployment and hires in the data with the distributions across sectors that would be chosen in this model by a planner, choosing optimally subject to the economy’s frictions (in the matching process) and constraints (no population growth, lower productivity of new hires, exogenous and endogenous job separations, exogenous Markov processes). The (only) advantage that the planner has, compared to the operation of the economy in the planner’s absence, is free mobility: The planner can costlessly move workers between sectors.

\(^5\) Sahin, Song, Topa and Violante (2012) incorporate sector-specific productivity shocks $z_{it}$, so existing workers’ overall production is $Z_{zit}$. This justifies mismatch indices allowing for productivity differences across sectors. They also modify the basic model to incorporate sector-specific job destruction rates $\delta_{it}$, sector-specific responses to aggregate productivity shocks, or endogenous separations. All would be possible future extensions to pursue in this paper, but are not included in the current version.
The planner’s choice of allocation is intuitively very obvious. It also turns out to be empirically easy to measure deviations from the planner’s chosen allocation, and it is these deviations that underlie the measure of mismatch. Denote the efficient level of unemployment in sector \( i \) at time \( t \) by \( u^*_it \), and the aggregate level of mismatch unemployment by \( u^M_t = \sum_{i=1}^I u^M_i = \sum_{i=1}^I (u^*_it - u^*_i) \).

Sahin, Song, Topa and Violante (2012) demonstrate the very intuitive result that an efficient allocation implies equalisation of the marginal value of an unemployed worker across sectors. In turn, this means that a planner will want to allocate unemployed workers across sectors so that the matching process gives rise to the same number of hires in all sectors. From the matching function, this indicates that

\[
\phi_i m_{it} \left( \frac{v^i_t}{u^*_it} \right) = \ldots = \phi_I m_{Ii} \left( \frac{v^I_t}{u^*_Ii} \right) = \ldots = \phi_I m_{Ii} \left( \frac{v^I_t}{u^*_Ii} \right)
\]

where the terms \( m_{it} \) denote the derivative of each sector-specific matching function with respect to local labour market tightness. It is worth noting that the result that hires respond to labour market tightness and are invariant to scale effects results from the assumption of constant returns to scale. As shown by Ellison, Keller, Roberts and Stevens (forthcoming), with decreasing returns to scale hires will depend additionally on the level of unemployment.

The planner wants more searchers in sectors with higher vacancies. And the planner will choose to allocate unemployed workers to sectors so that the sector-specific vacancy-unemployment ratio varies inversely with the sector-specific matching efficiency. Unemployment should be higher in a sector where match efficiency is better, because for a given level of vacancies that sector would generate more hires. The great feature of (27) is that it is static, despite arising from a dynamic and stochastic model of the labour market. This means it can readily be manipulated to give measures of deviation from the planner’s constrained optimum – measures that form the basis of the mismatch index used here.

To proceed to an index of mismatch embodying heterogeneity in matching efficiency it is necessary to make an assumption about the form of the matching function (26). For simplicity, and because it has prior empirical support, the matching function within each sector is assumed to be Cobb-Douglas with constant returns to scale, so that

\[
h^*_i = \Phi_i \phi_i v^a_i u^{1-\alpha}_i
\]

where \( \alpha \) is the vacancy share, common to all sectors.

Now consider the planner’s optimal choice of aggregate hires, given by the sum of (28) over sectors:

\[
h^*_i = \Phi_i v^a_i u^{1-\alpha}_i \left[ \sum_{i=1}^I \phi_i \left( \frac{v^i}{v^*_i} \right)^a \left( \frac{u^*_i}{u^*_i} \right)^{1-\alpha} \right]
\]
where the term in square brackets is the sum of the shares of total hires allocated to each sector. These shares are optimally chosen by the planner according to the efficient allocation (27). (27) implies an optimal-allocation condition in terms of the relative vacancy-unemployment ratios that should apply across any two sectors, \( i \) and \( j \):

\[
\frac{V_{ij}}{U_{ij}} = \left( \frac{\phi_j}{\phi_i} \right) \frac{1}{\alpha} \frac{V_{ji}}{U_{ji}}
\]

Summing across \( j \)s and rearranging gives a value for the planner’s chosen unemployment by industry:

\[
U^*_i = \left( \frac{\phi_i}{\sum_{i=1}^J \phi_i} \right) \frac{1}{\alpha} \frac{V_{ii}}{U_{ii}}
\]

Substituting (31) into (29) shows that total optimal hires can be simplified to

\[
h^*_i = \Phi_i \phi^*_i \frac{1}{\alpha} \frac{V_{ii}^{1-\alpha}}{U_{ii}^{1-\alpha}}
\]

where

\[
\phi^*_i = \left[ \sum_{i=1}^J \phi_i^* \left( \frac{V_{ii}}{V_{ii}} \right)^{1-\alpha} \right]^{\alpha}
\]

is a CES aggregator of the sector-level matching efficiencies, weighted by their vacancy share.

The number of actual hires implied by the matching function (28) parallels the planner’s optimal hires (29) above, the difference being that each sector’s unemployment is not optimally chosen:

\[
h_i = \Phi_i \phi_i V_{ii}^{1-\alpha} \left[ \sum_{i=1}^J \phi_i \left( \frac{V_{ii}}{V_{ii}} \right)^{\alpha} \left( \frac{U_{ii}}{U_{ii}} \right)^{1-\alpha} \right]
\]

As before, the term in square brackets sums the shares of total hires allocated to each sector, but here these shares can deviate from the efficient allocation given by condition (27).

The mismatch index \( \mathcal{W}_{H_i} \) – expression (2) in the main text – can then be derived using (32) and (34).

\[
\mathcal{W}_{H_i} = \frac{h_i^* - h_i}{h_i^*} = 1 - \sum_{i=1}^J \left( \frac{\phi_i}{\phi^*_i} \right) \left( \frac{V_{ii}}{V_{ii}} \right)^{\alpha} \left( \frac{U_{ii}}{U_{ii}} \right)^{1-\alpha}
\]
Appendix 2: Matching function estimation

The matching function (36) describes the key relationship between job finding and labour market tightness in each sector $i$:

$$\ln \left( \frac{h_{it}}{u_{it-1}} \right) = \ln \Phi_i + \ln \phi_i + \alpha \ln \left( \frac{v_{it}}{u_{it-1}} \right)$$ (36)

The hiring rate in sector $i$ is measured by the ratio of hires to unemployment in that sector. The number of hires per unemployed person in a sector will tend to be higher, the greater the ratio of vacancies in that sector compared to unemployment. $\alpha$ is the elasticity of hiring with respect to vacancies in sector $i$, which is assumed constant over industries. Variation across industries comes via sector-specific matching efficiencies $\phi_i$, which capture time-invariant sector differences in job finding rates. A quadratic time trend $\Phi_i$ embodies variation over time in the job finding rate caused by unobserved factors affecting all industries equally.

Hires into sector $i$, $h_{it}$, are the sum of all gross inflows into employment in $i$ during period $t$, including inflows from unemployment, from nonparticipation and by job movers from employment in a different sector. The divisor for hires is unemployment in sector $i$ at the start of time $t$ (captured empirically by the previous quarter’s stock of unemployed previously employed in $i$), which is a typical measure of the number of searchers looking for jobs in sector $i$, even though it means there is some dissonance between the scope of the hires measure and the scope of the searchers measure. The ratio of vacancies to unemployment in $i$ at the start of period $t$ proxies tightness in the sector-$i$ labour market, and is measured empirically by the ratio of the vacancy stock to the stock of unemployed during the previous quarter. For industry, occupation and region, hires and unemployment are calculated using the LFS. Information on vacancies comes from the Vacancy Survey at industry level and Jobcentre Plus for occupations and regions. The samples over which equation (36) is estimated are shown in Table 1.

The data do not reject the hypothesis that the matching function is Cobb-Douglas. Estimating a translog form $\ln h_{it} = \ln \Phi_i + \ln \phi_i + \alpha_1 \ln u_{it} + \alpha_2 \ln v_{it} + \gamma (u_{it} - v_{it})^2 + \epsilon_{it}$, the Cobb-Douglas restriction $\gamma = 0$ cannot be rejected. For example, for industry, the p-value is 0.48 and the point estimate of $\hat{\gamma} = 0.0092$ implies an elasticity of 1.009, very close to the Cobb-Douglas benchmark. Estimation of (36) gives a value for $\alpha$, the vacancy share in a Cobb-Douglas matching function (see Table 1).

Estimates of the vacancy share derived from comprehensive hiring, vacancy and unemployment data are reassuringly similar to previous UK estimates based on alternative data – and also very similar to values estimated or used in recent US work (Sahin, Song, Topa and Violante, 2012; Herz and van Rens, 2012; Borowczyk, Martins and Postel-Vinay, 2012).

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6 The empirical work proceeds on the basis that there are constant returns to scale, although the data appear to reject this in favour of decreasing returns in tests (see Petrongolo and Pissarides, 2001, for a review of previous similar tests on the matching function).
Sector fixed effects $\phi_i$ in part reflect each sector’s matching efficiency. The larger is the estimate of $\phi_i$, the faster, less costly and more efficient is matching: The rate at which unemployed workers are hired is higher, for any given level of labour market tightness (as measured by the vacancy-unemployment ratio). However, these fixed effects also reflect other unobserved sector-specific characteristics – for example, sectoral differences in the extent to which vacancy data represent actual vacancies.
Appendix 3: Data

Level of aggregation
The analysis in this paper measures misallocation across industry Sections, occupation Major Groups and standard Regions. The level of aggregation matters for the measured level of misallocation or mobility. For example, it is easier to move job without moving house, or to find an alternative job in a closely-related occupation, so mobility will be higher (and, presumably therefore, measured mismatch lower) across more disaggregated sectors. There are a number of reasons for using fairly high levels of aggregation. The first is simply data availability, particularly in relation to comprehensive UK vacancy data, which is available at 1 digit industry Section level. A further reason lies in the need to be able to accurately measure flows across the sectors chosen. Finally, there is the suspicion that shocks that impact importantly on mismatch typically occur at a fairly aggregated level. Jackman and Roper (1987) express a similar view: “we can work with data on administrative regions in the belief that regional imbalances constitute by far the largest single component of locational imbalance” (p.18). Previous studies find that there is no noticeable difference caused by increasing the level of aggregation, other than a reduced frequency of measured mobility (Longhi and Brynin, 2010; Parado, Caner and Wolff, 2007; Kambourov and Manovskii, 2008).

Unemployment
I construct data on unemployment by previous industry or occupation and current region of employment using quarterly Labour Force Survey (LFS) micro data. The LFS is a quarterly survey of a representative sample of UK households. Up to around 100,000 individuals are surveyed each quarter. Households remain in the sample for five quarters, unless they move address, with one fifth of the sample replaced each quarter. The definition of industry and occupation for those not in employment, relating to previous employment, is the only one available in LFS data. It entails excluding new entrants to unemployment or nonparticipation from the analysis of misallocation. Ideally one might want to measure unemployment by the segment in which the individual is searching, or the segment in which they eventually gain employment. Claimant Count unemployment data are available by usual and sought occupation (both shown in Figure 5), but stocks of claimant unemployment are very similar across these two definitions. In all cases, claimant count data on unemployment by occupation or region are analysed alongside stocks derived from the LFS.

Hires
I construct a measure of hires that most closely replicates the hires measure from JOLTS (the Job Openings and Labor Turnover Survey of establishments in the US). Hires are gross employment inflows, including from unemployment, nonparticipation, and job-to-job movers.\(^7\) Taking industry level data as an example, hires are defined in terms of destination industry (all hires into

\(^7\) Alternative measures of hires at the aggregate, occupation or region levels could be based on either Claimant Count unemployment outflows or Jobcentre Plus vacancy outflows. Neither is problem-free. An increasing proportion of those who leave the Claimant Count have failed to record their destination. From May 2006 there is no information about whether a Jobcentre Plus vacancy outflow was due to the vacancy (i) having been successfully filled by Jobcentre Plus clients, or (ii) having been withdrawn because it was filled through other recruitment channels, or (ii) remaining unfilled when it was automatically withdrawn because it had reached the closure date previously agreed with the employer.
Manufacturing, for example), and encompass all originating industries. The theoretical model behind the mismatch measures used here adopts the simplification that only unemployed workers search.

**Vacancies**

Vacancies by occupation and by region are NOMIS Jobcentre Plus data. The geography used for analysis by occupation and region is Great Britain, to correspond with the availability of Jobcentre Plus vacancy data. Jobcentre Plus data do not cover all vacancies, being more likely to omit skilled openings, and are also subject to possible discontinuities due to changes in vacancy handling procedures. There is a break in vacancies by occupation and by region in the early 2000s, when data are temporarily unavailable. The data I use relate to notified vacancies, which appear little affected by changes in Jobcentre Plus vacancy handling procedures in 2006. Jobcentres stopped following up vacancies after May 2006 and instituted automatic vacancy closure dates, which led to a sharp reduction in vacancies remaining live and unfilled after that time, but had little observable impact on the number of vacancies notified to Jobcentres.

Data on vacancies by industry are available from the ONS Vacancy Survey from April 2001. The Vacancy Survey classifies industries by Section according to the SIC2007 classification. ONS official Vacancy statistics take the form of a three-month rolling average. For the quarterly analysis in this paper, the three month average corresponding to each calendar quarter is used (January-March, April-June, July-September, October-December). Only seasonally adjusted data (using X12) are available from the ONS. The features of the Vacancy Survey determine the scope of the analysis by industry, which spans the UK and is based on the 18 industry Sections for which vacancy data are available.

**Classification changes**

There are two changes in occupational coding in the LFS, from SOC90 to SOC2000 in 2001q1 and again to SOC2010 in 2011q1. Data coded to SOC90 and SOC2010 have been recoded to SOC2000 at the unit group level using a technique that allocates individuals to a consistent unit group while maintaining a correct proportional mapping. I am very grateful to the LFS Survey Team and Sean Milburn in particular, who passed on code which enabled implementation of this technique. A mapping matrix was obtained from the ONS LFS Survey team for the SOC2010-SOC2000 recode, and I calculated a similar mapping matrix using information on job stayers over the quarter of the SOC90-SOC2000 change, namely the December-February 2000-2001 and March-May 2001 seasonal quarters.

I deal with the major change in industry classification, from SIC 2003 to SIC 2007 at the start of 2009, in a similar way, using a mapping matrix at 2-digit level available from the ONS based on the IDBR. Reclassified industry sectors are already provided in quarterly LFS datasets; these reclassified data maintain consistency by individual, but do not necessarily give proportions that are exact. There was a previous change in SIC during the sample period, from SIC 1992 to SIC 2003, but it involved only minor changes and had negligible impact at the two-digit level, so at this level, like the ONS LFS themselves, I treat SIC 1992 and SIC 2003 classifications as identical.

**Region**

The LFS region variable used is based on workplace location. The Claimant Count is an alternative source of regional unemployment data. Claimant Count figures cover only unemployed workers who claim Jobseekers Allowance, so are not comprehensive.