Unemployment and mismatch in the UK

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Abstract
This paper combines dynamic decompositions of unemployment movements with measures of labour market mismatch to estimate the impact of mismatch on UK unemployment. Mismatch is calculated to have been responsible for around half the UK unemployment rise during the financial crisis. Although mismatch appears to have returned to normal levels, its impact on the UK unemployment rate persists.

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

JEL codes: J6, E24, E32.

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1. Introduction

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. I argue in this paper that the UK's unemployment performance during the financial crisis gives at least as much cause for concern. I also suggest that special considerations apply to the UK labour market due to its low turnover compared to the US. Turnover dynamics do matter for the UK, which means that a dynamic model that takes account of the influence of mismatch on unemployment away from its steady state is needed.

This paper measures mismatch in the UK labour market using indices developed by Sahin, Sopa, Tong and Violante (2011). Mismatch captures the idea that it will be harder for the unemployed to get jobs if their skills and characteristics are less well matched to the requirements of available job openings. I use a basic index of mismatch that is wonderfully intuitive. It relies on the idea that a central planner would choose to allocate unemployed workers across sectors so that the ratio of unemployment to vacancies is the same in all sectors. Using estimates of industry matching functions, the index quantifies the extent to which mismatch across industries reduces hires. From this, it is possible to calculate the increase in unemployment due to mismatch.

In addition to providing new estimates of mismatch across industries for the UK, this paper's main aim is to explicitly tie measures of mismatch to unemployment dynamics. In this context, the important contribution is to incorporate a measure of actual (rather than steady state) unemployment dynamics, because the UK's low flow transition rates mean that unemployment only slowly approaches its steady state. By measuring how mismatch affects the path taken by unemployment towards steady state, this paper is able to draw conclusions about the extent to which higher mismatch has prolonged the duration of high unemployment and would reduce the impact of policy measures to bring it down.

Results indicate that mismatch is able to explain around half the movements in actual and steady state unemployment in the financial crisis. Estimates indicate that mismatch led to a substantial reduction in hires, equivalent to the typical annual net inflow into UK employment. Although mismatch indices have recovered to normal levels, there is no evidence that the impact of mismatch on actual UK unemployment has dissipated, reflecting the persistent effect of shocks that is a consequence of low UK turnover.

The paper proceeds as follows. The next section empirically and theoretically describes unemployment and its dynamics, emphasising the importance of looking at labour market flows. I first describe developments in the UK labour market, then set out the theoretical framework used to analyse unemployment. After describing evidence based on the Beveridge curve, I outline indices of labour market mismatch and how they can be used to analyse unemployment developments. Subsequent sections describe results and draw conclusions.

2. UK unemployment during the financial crisis

UK unemployment rose as demand dropped in the recession – but the rise in unemployment was lower than might have been expected (see Figure 1). UK unemployment started to rise rapidly from the second quarter of 2008, its rise beginning only one quarter after output began to fall. On the basis of the rapid 7% fall in UK output – which exceeded the demand drop in previous recessions – past experience suggested that the unemployment rate might reach its historical peaks of over 10%. It did not: the unemployment rate stopped rising, at just under 8%, in mid-2009. However, the post-recession rise in GDP (whereby, after the trough in 2009q2, GDP rose 3% over the subsequent five quarters) was not matched by a reduction in unemployment. Instead, the unemployment rate remained close to 8% for two years. The last half of 2011 has seen unemployment appear to pick up again (rising half of one percentage point – although estimates are subject to substantial measurement error as they are derived from surveys of individuals).

To understand the *proximate* drivers of this pattern of unemployment during the financial crisis, it is useful to look at data on flows of workers into and out of unemployment, before a formal analysis is presented in Section 2.2.

2.1. UK inflow and outflow rates during the financial crisis

A comparison of UK and US flow rates is instructive to shed light on how their movements account for changes in unemployment (see Figures 1, 2 and 3). In both the UK and US, all recessions over the last 40 years have been marked by a reduction in the outflow rate and an increase in the inflow rate.[1] During the recent financial crisis, the main reason why US unemployment rose so much higher than UK was the precipitous decline in the US job finding rate. (Remarkably, the peak in the US unemployment rate, after adjusting for changed labour force composition, was even higher than in the 1981 recession according to Elsby, Hobijn and Sahin, 2010.)

In both countries, inflow rate changes in the 2008-09 recession were fairly normal. However, more recently, the continued decline in the US inflow rate – to historically low and below-pre-recession levels – contrasts with the failure of the UK inflow rate to continue its very rapid initial recovery. The UK inflow rate has remained higher than before the recession, and the separation (E to U transition) rate has once again begun to rise markedly during 2011, which is not promising for future unemployment developments.

Recent UK-US contrasts in outflow rate movements are also notable. Whereas the US outflow rate has shown a fairly steady, although slow, recovery since 2010, UK outflow rates – and the job finding (U to E transition) rate in particular – have declined further.

Comparing the role of UK inflow and outflow rate changes in driving unemployment dynamics, Figures 1 and 3 demonstrate that the failure of the UK unemployment rate to fall much below 8% for two years was primarily due to a continued decline in the job finding rate, which counterbalanced the positive impact of declining inflows into unemployment. A topic of some importance, therefore, is to investigate reasons behind the behaviour of the job finding rate. At this point, it is worth highlighting the possible impact of mismatch on the unemployment rate and its dynamics.

[1] Although the UK Claimant Count does not show an increased inflow rate during 2011, its level and pattern might well be affected by recent structural changes to incentives and arrangements within the UK employment and benefits agency JobCentre Plus.

Misallocation of unemployed workers across sectors, in relation to available job opportunities, will make it harder for them to find jobs: Mismatch lowers the job finding rate. The extent to which the UK job finding rate reflects the influence of mismatch, and its impact on unemployment, will be estimated in this paper.

The recent rise in unemployment is a reflection of further declines in the job finding rate and apparent new adverse developments in the rate of job loss.

The next section sets out a formal method of assessing the relative roles of inflow and outflow rates, which will also be used in later analysis of the role of mismatch.

2.2. Unemployment dynamics, job finding and job loss: Decomposing actual unemployment dynamics

What is the relative importance of outflows compared to inflows in recent unemployment movements?

Start from the law of motion for the stock of unemployment U_t, expressed in discrete time, and for simplicity consider a two state model in which a worker can be either employed or unemployed. Next period's unemployment will be equal to unemployment this period, plus gross inflows, and minus gross outflows:

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

where s_t is the unemployment inflow rate (assumed constant during t) and f_t is the outflow rate. Expressing (1) in terms of the unemployment rate $u_t = U_t / L_t$, and using $E_t / L_t = e_t = 1 - u_t$ (making the simplifying assumption that the labour force has constant size) gives:

$$u_{t+1} = u_t + s_t\left(1 - u_t\right) - f_t u_t \tag{2}$$

By rearranging (2) it can be shown that actual unemployment rate u_{t+1} will be well approximated by its steady state value $\bar{u}_t = s_t / \left(f_t + s_t\right)$ if flow transition rates f_t and s_t are high, or if changes in these flow transition rates are small (implying that Δu_{t+1} is small):

$$u_{t+1} = \frac{s_t}{f_t + s_t} - \frac{1}{f_t + s_t}\Delta u_{t+1} \tag{3}$$

For the US, flow transition rates are sufficiently high that it has been very reasonable to assume that actual unemployment is well approximated by its steady state – so the second term on the right hand side of (3) can justifiably be ignored. However, this is not true for the UK and holds even less well for continental European countries (see Hertweck and Sigrist, 2012, on Germany; Elsby, Hobijn and Sahin, forthcoming, present evidence for a wide range of OECD countries). The US monthly inflow rate has averaged 0.539 between 1970 and the beginning of 2012, and the US monthly outflow rate has averaged 0.035 (based on duration data – see Figure 2). In contrast, duration data derived from the LFS indicates that the UK monthly inflow rate has been 0.131 on average since 1975, with a mean monthly outflow rate of 0.009 (these UK estimates are based on available data which are biennial prior to 1984, annual until 1992 and quarterly thereafter; Figure 3 shows that flow rates based on unemployed benefit claimants take similar values).

The empirical importance of the final term in (3) for the UK, and its unimportance in the US, can be seen in Figure 4, where actual and steady state unemployment rates are plotted for both countries. As noted by Hall (2005), these correspond very closely in the US – except near the peak unemployment rate of the latest financial crisis. That peak exhibits a feature notable throughout the last 35 years in the UK: Steady state unemployment acts as a leading indicator, when flow transition rates are low enough that dynamics play an important role. The latest UK data exhibit the disturbing discrepancy that the steady state rate has risen rapidly and lies well above the actual rate, which presages further rises in actual unemployment over the next few quarters.

One way of quantifying this difference in the role of non-steady state dynamics in the US versus the UK is to contrast the *half-life* of any deviation from steady state, calculated as $\ln(2)/(f_t + s_t)$. The half-life of a deviation from steady state is 4.9 months in the UK, compared to 1.2 months in the US (based on $f_t + s_t$ of 0.574 for the US and 0.141 for the UK).

Because shocks that drive UK unemployment away from steady state will have a noticeably persistent effect, it is worthwhile including these non-steady state dynamics explicitly in an assessment of the relative impact of inflow and outflow rates on unemployment changes. Elsby, Hobijn and Sahin (forthcoming) and Smith (2011) show how this can be done, by manipulating (3) to give an expression relating the change in actual unemployment to its own lag and the change in the steady state unemployment rate. The two decompositions are very similar, the key difference being that Elsby, Hobijn and Sahin work with log changes and Smith with levels.

Smith (2011) shows that

$$\Delta u_{t+1} \approx \left(\frac{\omega_{t+1} s_t}{\omega_{t+1}^2 + \omega_t} \right) \frac{\Delta \bar{u}_{t+1}}{\bar{u}_t} + \left(\frac{\omega_{t+1}}{\omega_{t+1}^2 + \omega_t} \right) \Delta u_t \tag{4}$$

where $\omega_t = f_t + s_t$. This is a recursive expression relating actual and steady state unemployment dynamics, which is useful because the percentage change in steady state unemployment, $\Delta \bar{u}_{t+1} / \bar{u}_t$, can be readily decomposed into a part due to changes in the inflow rate, $\bar{C}_{t+1}^s$, and a part due to changes in the outflow rate, $\bar{C}_{t+1}^f$. Based on Petrongolo and Pissarides (2008),

$$\frac{\Delta \bar{u}_{t+1}}{\bar{u}_t} \approx \underbrace{(1 - \bar{u}_t) \frac{\Delta s_{t+1}}{s_t}}_{\bar{C}_{t+1}^s} \underbrace{- (1 - \bar{u}_t) \frac{\Delta f_{t+1}}{f_t}}_{\bar{C}_{t+1}^f} \tag{5}$$

Then, substituting (5) into (4) and iterating backwards *ad infinitum* gives a decomposition of changes in actual unemployment into a contribution attributable to the inflow rate and a part due to the outflow rate:

$$\Delta u_{t+1} = C_{t+1}^s + C_{t+1}^f \tag{6}$$

where

$$C_{t+1}^{s}=\left(\frac{\omega_{t+1}s_{t}}{\omega_{t+1}^{2}+\omega_{t}}\right)\bar{C}_{t+1}^{s}+\left(\frac{\omega_{t+1}}{\omega_{t+1}^{2}+\omega_{t}}\right)C_{t}^{s} \tag{7}$$

and similarly for C_{t+1}^{f}. In practice, in order to recursively calculate these contributions, an assumption must be made about initial conditions, and I will assume $C_{0}^{0}=u_{t}-\bar{u}_{t}$, as well as $C_{0}^{s}=C_{0}^{f}=0$. The recursive structure implies a persistent but declining contribution of the initial condition, since $C_{t+1}^{0}=\left[\omega_{t+1}/\left(\omega_{t+1}^{2}+\omega_{t}\right)\right]C_{t}^{0}$.

The framework can be extended to examine the particular roles of the job finding rate – the flow transition rate from unemployment to employment – and the separation rate – from employment to unemployment. Denote the number of unemployed workers in any given quarter t who are employed in the subsequent quarter by UE_{t} (so UE_{t} is the gross job finding flow during t). The job finding flow transition rate is equal to UE_{t}/U_{t}, where U_{t} is the stock of unemployment at the start of period t.

Note that, from the laws of motion of unemployment, employment and nonparticipation in a three-state model, the steady state unemployment rate can be expressed as follows:

$$\bar{u}_{t}=\frac{\lambda_{t}^{EU}+\lambda_{t}^{ENU}}{\lambda_{t}^{UE}+\lambda_{t}^{UNE}+\lambda_{t}^{EU}+\lambda_{t}^{ENU}}=\frac{s_{t}}{f_{t}+s_{t}} \tag{8}$$

where the total outflow rate, f_{t}, is the sum of the job finding rate, $\lambda_{t}^{UE}\equiv UE_{t}/U_{t}$, and the rate of flow taking workers indirectly from employment to unemployment via nonparticipation, $\lambda_{t}^{UNE}=\lambda_{t}^{UN}\lambda_{t}^{NE}/\left(\lambda_{t}^{NU}+\lambda_{t}^{NE}\right)$. To understand λ_{t}^{UNE} intuitively, note that it can be viewed as the product of the probability of moving from unemployment to nonparticipation (transition rate λ_{t}^{UN}) and the likelihood of (subsequently) flowing from nonparticipation to employment (given in terms of transition rates by $\lambda_{t}^{NE}/\left(\lambda_{t}^{NU}+\lambda_{t}^{NE}\right)$). Similarly, the total inflow rate, s_{t}, consists of the separation rate, λ_{t}^{EU} and the flow rate from employment to unemployment via nonparticipation, $\lambda_{t}^{ENU}=\lambda_{t}^{EN}\lambda_{t}^{NU}/\left(\lambda_{t}^{NU}+\lambda_{t}^{NE}\right)$.

Each of the four terms making up inflow and outflow rates can be allocated a contribution to actual unemployment dynamics that mirrors (7) in form.

2.2.1. A log decomposition

The decomposition of Smith (2011), described above, has the advantage that working in 'levels' (actual unemployment rate dynamics) gives a straightforward decomposition into influences of additive components. However, there is also an advantage to working with a decomposition of *log* unemployment dynamics, as in Elsby, Hobijn and Sahin (forthcoming), in that the log transformation acts to smooth variations. Results from 'levels' and 'log' decompositions are very similar, of course, though small differences do arise due to the different approximations made.

Because of the ease of working with logarithms, in the empirical work of this paper the log decomposition developed by Elsby, Hobijn and Sahin (forthcoming) is used:

$$\Delta \ln u_{t+1} = \rho_t \left[(1-\bar{u}_t)(\Delta \ln s_{t+1} - \Delta \ln f_{t+1}) \right] + \rho_t \frac{1-\rho_{t-1}}{\rho_{t-1}} \Delta \ln u_t \tag{9}$$

where $\rho_t = 1 - \mathrm{e}^{-(f_t + s_t)}$ is the sum of inflow and outflow probabilities during t. The term in square brackets captures contributions to changes in log *steady state* unemployment, coming via current shocks to inflow and outflow rates. The second term on the right hand side embodies the impact of past shocks to these flow rates. (See Elsby, Hobijn and Sahin, forthcoming, or Appendix C of Smith, 2011, for derivation and discussion of the non-steady state log decomposition.)

The log decomposition highlights a useful rule of thumb, noted by Elsby, Michaels and Solon (2009): A good indicator of the relative importance of inflow and outflow rates is their log changes. This is evident from the first term on the right hand side of (9) (noting that $1-\bar{u}_t \approx 1$). It is the reason why transition rates are graphed using logarithmic scales in Figures 2 and 3, since this gives an accurate picture of their influence.

2.3. Results from a dynamic decomposition of unemployment movements into inflow and outflow influences

To begin with, it is worth confirming empirically that UK unemployment dynamics are best described using a non-steady state model.

The top panel of Figure 5 compares predicted values of log changes in the unemployment rate from two models, one including and one ignoring non-steady state dynamics (in each case, using a logarithmic version of the relevant decomposition). The steady state model is that of Fujita and Ramey (2009) and Elsby, Michaels and Solon (2009). It uses only the term in square brackets in (9), thus proposing that $\Delta \ln u_{t+1} \approx (1-\bar{u}_t)(\Delta \ln s_{t+1} - \Delta \ln f_{t+1})$. The non-steady state model fits changes in the actual UK unemployment rate very closely, unlike the steady state model.[2]

To see the relative contributions to unemployment dynamics, a useful summary statistic is the 'beta' outlined by Fujita and Ramey (2009):

$$\beta = \frac{\mathrm{cov}(C_t, \Delta u_t)}{\mathrm{var}(\Delta u_t)} \tag{10}$$

where C_t is one of the contributions to unemployment dynamics defined in section 2.2. Various betas of interest are shown in Table 1.

Numerically, the non-steady state model explains 82% of actual changes in log unemployment (see Table 1). Log changes in outflow and inflow rates have roughly equal contributions to actual unemployment dynamics, with outflow rate changes accounting for 42% and inflow rate changes

[2] Hertweck and Sigrist (2012) demonstrate that German unemployment also requires a non-steady state model to adequately describe its dynamics, and Elsby, Hobign and Sahin (forthcoming) do likewise for other continental European countries.

accounting for 40%. So, inflow and outflow rates appear to have about the same importance in unemployment movements.

The remaining 18% of actual unemployment dynamics is accounted for by the initial condition (which contributes less than 2%) and a residual. The residual arises in part due to fairly small sample size, violation of assumptions (linearity, constant labour force, constancy of flow transition rates within quarters). The residual might also be related to a well-known inconsistency between stocks and flows as measured by micro data (due to misclassifications, missing data, or time aggregation, for example). The discrepancy between stocks and flows causes a difference between the levels of the fitted values, constructed using flows data, and the actual unemployment rate – this difference is apparent in the lower panel of Figure 5. Despite this, the better fit of the non-steady state model's predicted unemployment rate compared to that of the steady state model can be seen (which is a corollary of the non-steady state model's better fit to actual unemployment rate dynamics). Figure 5 makes clear that a stock-flow discrepancy does not affect changes, only levels. It will appear again later in the paper in the estimate of the unemployment rate under the counterfactual of no mismatch, but it plays no role elsewhere and does not affect estimates of dynamic contributions.

The non-steady state decomposition also enables an estimate of the relative importance of *innovations*, in the form of shocks to flow transition rates, compared to the impact of *past shocks*, as described in Section 2.2. Roughly 60% of explained variation comes through current shocks (see Table 1, where the total contribution of flow rate innovations is 0.48, compared with an explained proportion of actual unemployment dynamics of 0.82). It is striking that *past* shocks account for as much as 40% of *current* unemployment movements (whose proximate cause can be identified). Again this illustrates the importance of persistence in the UK labour market. Interestingly, innovations form a relatively larger part of the influence of inflow rates, consistent with the rapid response of UK unemployment to the increased inflows seen in 2008. Past shocks to inflow rates account for only 15% of actual unemployment dynamics, compared to 20% for past shocks to outflow rates. This is an indication that in order to understand why UK unemployment has remained stubbornly high, it is necessary to look further at outflow rates in particular, and highlights the potential importance of mismatch.

Splitting flow rates to distinguish job finding and job loss rates from flows involving nonparticipation is instructive. The direct flows between unemployment and employment dominate nonparticipation flows in accounting for unemployment movements, each explaining about one third. The final line of Table 1 highlights the large lagged impact of job finding shocks, which are equally as influential in unemployment dynamics as current job finding shocks. The impact of separation rate shocks appears to fade relatively quickly, but because the separation rate is estimated to have a slightly bigger overall impact than the job finding rate, past separation shocks are nevertheless almost as influential as past job finding shocks in affecting unemployment.

I next turn to the role of mismatch in unemployment dynamics, which perhaps takes on greater importance in view of the large role of outflow and job finding rate changes on the dynamics and persistence of UK unemployment.

3. A first look at mismatch during the financial crisis: The Beveridge curve

The Beveridge curve expresses the relationship between unemployment and vacancies, a relationship that will reflect 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. Figure 6 plots UK and US Beveridge curves. As is usual, vacancies and unemployment are both expressed as ratios of the labour force.

Both countries had a similar experience during the recession: The fall in demand was accompanied by a reduction in the vacancy rate and a rise in the unemployment rate. During the recession, both economies appear to have moved south east along stable Beveridge curves. The slope of the curve is very similar in the two countries. Over a comparable pre-recession period, the UK unemployment rate rose 3.5 percentage points for each 1 percentage point decline in the vacancy rate, while this 'trade-off' between vacancies and unemployment was 3.7 in the US.

Subsequent movements in the US Beveridge curve during the financial crisis have raised controversial questions and inspired substantial US research (to date, less for the UK). After the recession ended, the US vacancy rate recovered, but the unemployment rate appeared not to fall. This suggested a possible increase in structural unemployment, which could be a result of a rise in mismatch. Revisions to the US Job Openings and Labor Turnover Survey (JOLTS) vacancy data have changed the picture a little, but it remains the case that the US labour market has departed from its pre-2009 Beveridge curve path: The US Beveridge curve does appear to have shifted upwards. One key question that has been addressed in recent research is whether this shift will be temporary, or whether it reflects an increase in the structural, or natural, unemployment rate. A further controversy has centred over the role of policy, with some in the Federal Reserve attributing at least some of the higher unemployment to mismatch, and opining that monetary policy could play no role in reducing such structural unemployment.[3]

The UK Beveridge curve looks far less exciting, at first glance. The Great Moderation in the 2000s was accompanied by great stability in vacancy creation and unemployment. But just as in the US, as vacancies fell in the recession, so unemployment rose. The UK has been relatively poor at generating job openings post-recession, so not surprisingly the unemployment rate has not fallen.

But further investigation reveals that the UK's Beveridge curve is in fact very similar to that of the US – it's just that, as in many other fields, the US does things on a larger scale. Looking more closely at the post-recession UK Beveridge curve reveals a hidden, and not very pleasant, picture (Figure 7). Between the end of the recession in 2009q2 and the end of 2010, the UK vacancy rate actually increased by 14%. But the unemployment rate did not fall. The UK Beveridge curve remained vertical until mid-2011.

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[3] For example, Narayana Kocherlakota, President of the Federal Reserve Bank of Minneapolis, said in a speech in Minneapolis on 10 May 2012 that central bankers must "contemplate the possibility that the erosion in labour market performance that we've seen in the United States over the past five years may be highly persistent, even under appropriate monetary policy", and suggested that accelerating US inflation is "a signal that our country's current labour market performance is much closer to 'maximum employment' than the post-World War II US data alone would suggest" (quoted by Bloomberg: http://www.bloomberg.com/news/2012-05-10/fed-s-kocherlakota-sees-persistent-damage-to-job-market.html).

Between mid-2011 and early 2012, the vacancy rate was stable, but unemployment rose. This recent *rightward* shift is probably due to the increased inflow rate (evident in the *E* to *U* separation rate in Figure 3). As explained by Blanchard and Diamond (1989) and reiterated recently by Daly, Hobijn, Sahin and Valetta (forthcoming), a rise in layoffs can initiate a counter-clockwise Beveridge curve loop by increasing unemployment; then as demand recovers and layoffs diminish there is a simultaneous increase in vacancies and a fall in unemployment.[4]

For the UK, as in the US, the discouraging Beveridge curve movements leave open the possibility that there have been adverse changes in mismatch. The next sections show how mismatch and its relationship with unemployment can be measured, before turning to empirical estimates of the impact of mismatch.

4. Derivation of mismatch indices

The mismatch indices used in this paper are drawn from Sahin, Sopa, Tong and Violante (2011). The indices are 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. Exogenously-determined vacancies v_i in market i are filled (only) by unemployed workers u_i searching in that market. Hires h_i are determined by a matching function embodying frictions:

$$h_i = \Phi_t \phi_i m\left(u_i, v_i\right) \tag{11}$$

where m is increasing and strictly concave in both arguments and homogenous of degree one in $\left(u_i, v_i\right)$. Scalar ϕ_i measures matching efficiency in sector i, which reflects matching frictions in that sector. Φ_t captures aggregate changes over time in matching efficiency.

Further assumptions are that firms face a sector-specific exogenous vacancy posting cost that determines v_i, matches are exogenously destroyed at rate δ, and existing workers produce Z units of output, where δ and Z are aggregate shocks following a joint Markov process. 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. Assuming that the economy has measure one of agents, who can be employed, unemployed, or out of the labour force l, the

[4] Hall (2010) noted an alternative rationale for a counter-clockwise loop (though one that involves an initial upward, rather than an outward, movement): The ratio of the hiring rate to matching efficiency tends to be low in contractions and high in recoveries.

[5] Sahin, Song, Topa and Violante (2011) incorporate sector-specific productivity shocks z_i, so existing workers' overall production is Zz_i. This enables them to produce mismatch indices allowing for productivity differences across sectors. That would be a possible future extension to pursue in this paper, but is not included in the current version. Sahin, Song, Topa and Violante's (2011) conclusions are not much changed by allowing for sector-specific productivities.

volume of unemployment $u = l - \sum_{i=1}^{I} e_i$ is given. However, 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 indices 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. Note that, because the planner's search is costless, the planner will choose that everyone will participate in the labour force.

It turns out that the planner's chosen allocation is intuitively very obvious. It also turns out to be empirically very easy to measure deviations from the planner's chosen allocation, and it is these deviations that form the measures 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

$u_t^M = \sum_{i=1}^{I} u_{it}^M = \sum_{i=1}^{I} \left(u_{it}^* - u_{it} \right)$.

Sahin, Song, Topa and Violante (2011) demonstrate the very intuitive result that an efficient allocation implies equalisation of the marginal value of an unemployed worker across sectors. In turn, this implies 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 implies that

$$\phi_1 m_{u_1}\left(\frac{v_1}{u_1^*}\right) = \ldots = \phi_i m_{u_i}\left(\frac{v_i}{u_i^*}\right) = \ldots = \phi_I m_{u_I}\left(\frac{v_I}{u_I^*}\right) \qquad (12)$$

where the terms m_{u_i} denote the derivative of each sector-specific matching function with respect to local labour market tightness (only, due to the assumption of constant returns to scale).

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 (12) 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 indices used here.

Rearranging (12) gives rise to a version of the index of "structural unemployment" described and estimated in Jackman and Roper (1987), generalised for heterogeneity in matching efficiency. Jackman and Roper (1987) assumed constant matching efficiency, in which case (12) rearranges to give their index of "structural" unemployment (due to mismatch):

$SU_t = u_t^M = 0.5\sum_{i=1}^{I}\left|\left(u_{it}/u_t\right)-\left(v_{it}/v_t\right)\right|u_t$. Without heterogeneity in matching efficiency, the planner would wish to *equalise* unemployment-vacancy ratios across sectors. Equivalently, the planner would require zero deviation between each industry's unemployment and vacancy shares (setting $\left(u_{it}/u_t\right)-\left(v_{it}/v_t\right)=0,\ \forall i$). The Jackman-Roper *SU* index is not a focus of this paper largely because the data support heterogeneity in matching efficiency.

A simple implication of (12) and the *SU* index is worth noting, however: Mismatch will be reflected in the correlation between unemployment and vacancy shares across sectors. A lower correlation implies increased mismatch, with a perfect correlation of 1 corresponding to no mismatch. Using this to take a first look at data for 18 UK industry sections reveals a dramatic fall in the correlation between unemployment and vacancy shares after 2008 (see Figure 8). This indicates that labour market mismatch measured across UK industries increased substantially during the financial crisis. The correlation fell from a pre-recession high of 0.86 in the first quarter of 2008 to a low point of 0.61 in the second quarter of 2010. However, this simple correlation seems to have encouraging implications about the enduring effects of mismatch: From 2010, the correlation rose back towards its peak fairly rapidly, reaching 0.82 in the third quarter of 2011 – although it has subsequently fallen back. It is of interest to compare these numbers to those reported by Sahin, Song, Topa and Violante (2011) for the US, across a very similar range of 17 industries and based on quite comparable data. The US correlation peaked in 2006 at a lower level than the UK's high point – 0.75 – and subsequently fell during the financial crisis to a deeper trough of 0.45, before rising to around 0.65 at the end of their sample in mid-2011. Thus, perhaps surprisingly, US cross-industry correlations are suggestive of greater mismatch in normal times, and perhaps also of a greater adverse impact from the financial crisis. (The larger are cross-country differences in matching efficiencies, the less valid are cross-country comparisons, but later results in this paper reveal substantial similarity in estimated matching efficiencies between US and UK industries).

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 (11). For simplicity, and because it has substantial prior empirical support, the matching function within each sector is assumed to be Cobb-Douglas with constant returns to scale, so that

$$h_{it} = \Phi_t \phi_i v_{it}^{\alpha} u_{it}^{1-\alpha} \tag{13}$$

Now consider the planner's optimal choice of aggregate hires, given by the sum of (13) over sectors:

$$h_t^* = \Phi_t v_t^{\alpha} u_t^{1-\alpha}\left[\sum_{i=1}^{I}\phi_i\left(\frac{v_{it}}{v_t}\right)^{\alpha}\left(\frac{u_{it}^*}{u_t}\right)^{1-\alpha}\right] \tag{14}$$

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 condition (12).

At this point it is useful to consider what the optimal-allocation condition implies in terms of a comparison of vacancy-unemployment ratios between two sectors, i and j, namely that

$$\frac{v_{it}}{u_{it}^{*}} = \left(\frac{\phi_j}{\phi_i}\right)^{\frac{1}{\alpha}} \frac{v_{jt}}{u_{jt}^{*}} \tag{15}$$

Summing across j s and rearranging gives a value for the planner's chosen unemployment by industry:

$$u_{it}^{*} = \left(\frac{\phi_i}{\sum_{i=1}^{I}\phi_i}\right)^{\frac{1}{\alpha}} \frac{v_{it}}{v_t} u_t \tag{16}$$

Substituting (16) into (14) shows that total optimal hires can be simplified to

$$h_t^{*} = \Phi_t \bar{\phi}_t v_t^{\alpha} u_t^{1-\alpha} \tag{17}$$

where

$$\bar{\phi}_t = \left[\sum_{i=1}^{I} \phi_{it}^{\frac{1}{\alpha}} \left(\frac{v_{it}}{v_t}\right)\right]^{\alpha} \tag{18}$$

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 (13) parallels the planner's optimal hires (14) above, the difference being that each sector's unemployment is not optimally chosen:

$$h_t = \Phi_t v_t^{\alpha} u_t^{1-\alpha} \left[\sum_{i=1}^{I} \phi_{it} \left(\frac{v_{it}}{v_t}\right)^{\alpha} \left(\frac{u_{it}}{u_t}\right)^{1-\alpha}\right] \tag{19}$$

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 (12).

Now the key mismatch index can be defined. $\mathcal{M}_{\phi t}^{h}$ measures the proportion by which actual hires are below the optimal level:

$$\mathcal{M}_{\phi t}^{h} = \frac{h_t^{*} - h_t}{h_t^{*}} = 1 - \sum_{i=1}^{I} \left(\frac{\phi_{it}}{\bar{\phi}_t}\right) \left(\frac{v_{it}}{v_t}\right)^{\alpha} \left(\frac{u_{it}}{u_t}\right)^{1-\alpha} \tag{20}$$

In the empirical work below, a version of this mismatch index will be shown that calculates the effect of mismatch on hires as the proportionate increase in actual hires that would arise if there were no mismatch, which is given by $\mathcal{M}_{\phi t}^{h} \big/ \left(1 - \mathcal{M}_{\phi t}^{h}\right)$.

5. The impact of mismatch on the level and dynamics of unemployment

5.1. Mismatch and job finding

Fundamentally, the impact of mismatch on unemployment and its dynamics arises because mismatch reduces the job finding rate. The impact of mismatch on job finding rates can be calculated using $\mathcal{M}_{\phi t}^{h}$, the index capturing the proportionate reduction in hiring rates due to mismatch.

The job finding rate is defined as

$$f_t = \frac{h_t}{u_t} \tag{21}$$

Taking the number of actual hires from (19) and using expression (20) for $\mathcal{M}_{\phi t}^{h}$, the job finding rate can be written:

$$f_t = \left(1 - \mathcal{M}_{\phi t}^{h}\right)\Phi_t\left(\frac{v_t}{u_t}\right)^{\alpha} \tag{22}$$

The job finding rate in the absence of mismatch is the planner's optimal job finding rate, given by

$$f_t^* = \frac{h_t^*}{u_t^*} = \Phi_t\left(\frac{v_t}{u_t^*}\right)^{\alpha} = \frac{f_t}{\left(1-\mathcal{M}_{\phi t}^{h}\right)}\left(\frac{u_t}{u_t^*}\right)^{\alpha} \tag{23}$$

5.2. Mismatch and unemployment

5.2.1. The no-mismatch unemployment rate

The dynamic path of the no-mismatch unemployment rate can then be described by a recursive expression, a rearrangement of (2), but based on the no-mismatch job finding rate:

$$u_{t+1}^* = s_t + \left(1 - s_t - f_t^*\right)u_t^* \tag{24}$$

where the initial condition is defined as $u_0^* = \overline{u}_0^*$.

5.2.2. The impact of mismatch on the steady state unemployment rate

The contribution of mismatch to the *level* of unemployment is most easily measured in terms of the effect on the steady state unemployment rate, $\overline{u}_t = s_t / \left(f_t + s_t\right)$. By lowering f_t, mismatch will directly raise $\overline{u}_t$. As discussed in Sahin, Song, Topa and Violante (2011), there is also an indirect effect, since mismatch also increases the impact of any change in s_t. Intuitively, this is because a lower outflow rate means that any rise in the inflow rate will boost $\overline{u}_t$ by more, because workers remain in the unemployment pool for longer. Algebraically, this is shown by $d\overline{u}/dfds = (s-f)/(s+f)^3 < 0$ since $f \gg s$.

The relative contribution of mismatch to *changes* in the (log) steady state rate can also be readily assessed. Start with the basic relationship between steady state unemployment rates:

$$\bar{u}_t = \bar{u}_t^* + \left(\bar{u}_t - \bar{u}_t^*\right) \tag{25}$$

The steady state rate $\bar{u}_t$ is made up of a part reflecting non-mismatch shocks – the no-mismatch steady state rate $\bar{u}_t^*$ – and a part reflecting mismatch shocks, $\left(\bar{u}_t - \bar{u}_t^*\right)$. Taking log differences demonstrates that the log change in the steady state rate is a share-weighted sum of the log changes of the two terms in (25):

$$\Delta \ln \bar{u}_t \approx \frac{\bar{u}_t^*}{\bar{u}_t} \Delta \ln \bar{u}_t^* + \frac{\left(\bar{u}_t - \bar{u}_t^*\right)}{\bar{u}_t} \Delta\left(\ln \bar{u}_t - \ln \bar{u}_t^*\right) \tag{26}$$

A variance decomposition using (26) will give the relative contributions to steady state unemployment dynamics of mismatch shocks and non-mismatch shocks. These relative contributions can be expressed as 'betas', giving the average variance contribution over some period (along the lines of Fujita and Ramey, 2009). Alternatively, the period-by-period relative contributions could be assessed by graphing cumulative sums of each of the two terms on the right hand side of (26), choosing some relevant period (such as the start of a recession or a recovery) as a base.

5.2.3. The impact of mismatch on actual unemployment rate dynamics: How does mismatch alter the impact of labour market shocks?

In this section I highlight the facts that mismatch alters the effect of any given current shock involving inflow and outflow rates, as well as changing the persistence of unemployment through the recursive term.

The analysis is conducted using expression (9) to show how the innovation and recursive coefficients in the expression for log actual unemployment dynamics are affected by mismatch through the outflow rate f_t. (9) is repeated here for ease of reference:

$$\Delta \ln u_{t+1} = \rho_t \left(1 - \bar{u}_t\right)\left[\Delta \ln s_{t+1} - \Delta \ln f_{t+1}\right] + \rho_t \frac{1 - \rho_{t-1}}{\rho_{t-1}} \Delta \ln u_t \tag{9}$$

where $\rho_t = 1 - \exp^{-(f_t + s_t)}$ and $\bar{u}_t = s_t / \left(f_t + s_t\right)$. The innovation coefficient is $\rho_t\left(1 - \bar{u}_t\right)$, and the recursive coefficient is $\rho_t\left(1 - \rho_{t-1}\right) / \rho_{t-1}$.

Greater mismatch, reducing the outflow rate f_t, raises $\bar{u}_t$ so lowers $1 - \bar{u}_t = f_t / \left(f_t + s_t\right)$ – but not by much, because $f_t \gg s_t$: $1 - \bar{u}_t$ will fall only slightly further below unity. Mismatch also reduces ρ_t (which is the sum of the probabilities of inflow and outflow, the latter being reduced by mismatch). So, greater mismatch will reduce the impact of current shocks through the innovation coefficient. The actual innovation coefficient will be lower than the no-mismatch case.

The recursive coefficient can be rearranged as $\left(\rho_t/\rho_{t-1}\right)-\rho_t$. A *permanent* change in mismatch would increase the recursive coefficient. A *temporary* change in mismatch will tend to reduce the recursive coefficient below unity as mismatch worsens, then raise it above unity as the outflow rate recovers when mismatch dissipates.[6]

To summarise: 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.

6. Results

6.1. Matching function estimation

The matching function (27) describes the key relationship between the log ratio of hires to unemployment in industry i, $\ln\left(h_{it}/u_{it}\right)$, and labour market tightness in that industry as measured by the log ratio of vacancies to unemployment $\ln\left(v_{it}/u_{it}\right)$:

$$\ln\left(\frac{h_{it}}{u_{it}}\right)=\ln\Phi_t+\ln\phi_i+\alpha\ln\left(\frac{v_{it}}{u_{it}}\right) \tag{27}$$

Equation (27) is estimated using quarterly panel data on 18 UK industries since 2001q3. These industries cover the whole economy apart from Agriculture, forestry and fishing, Households as employers and Extra-territorial organisations (Sections A, T and U). Industries are measured by Sections in the current SIC 2007 classification. Using quarterly Labour Force Survey (QLFS) micro data, a measure of hires is calculated to mirror the JOLTS hires measure that is most commonly used in recent studies of the US labour market. This captures total hires into industry i, including hires from employment, unemployment and nonparticipation. Hires are measured on the basis of flows during the current quarter, and stocks of unemployment and vacancies are given by their values in the previous quarter. Using QLFS data, unemployment is calculated on the basis of previous industry, and current vacancies by industry are taken from the comprehensive Office for National Statistics (ONS) Vacancy Survey. More detailed descriptions of data used can be found in the Appendix. I do not seasonally adjust the unemployment or hires data to avoid bias due to smoothing, so seasonal (quarterly) dummies are included. Vacancy data are publicly available only on a seasonally adjusted basis (using X12).

The data do not reject the hypothesis that the matching function is Cobb-Douglas. Estimating a translog form $\ln h_{it}=\ln\Phi_t+\ln\phi_i+\alpha_1\ln u_{it}+\alpha_2\ln v_{it}+\gamma\left(u_{it}-v_{it}\right)^2+\varepsilon_{it}$, the Cobb-Douglas

[6] Changes in the recursive coefficient depend, in opposite directions, on the speed of any change in the outflow rate (through the term in parentheses) as well as its change (the second term). Numerically, the term in parentheses dominates. $\left(\rho_t/\rho_{t-1}\right)$ would be unity if flow transition rates were stable. Over 2000-2011 in the UK they typically varied between 0.95 and 1.05, but declined below 0.9 as the outflow rate fell rapidly during the recession. ρ_t itself fell from a stable 0.14 between 2000 and 2005 to around 0.08 in 2011, exhibiting similar dips and recoveries to the outflow rate during 2005-07 and 2008-10 (see Figure 10).

restriction $\gamma = 0$ cannot be rejected (p-value 0.48) and the point estimate of 0.0092 implies an elasticity of 1.009, very close to the Cobb-Douglas benchmark.[7]

α represents the vacancy share in a Cobb-Douglas matching function. α is the elasticity of hiring with respect to vacancies in industry i, and so is related to the rate at which vacancies are filled. Estimation of (27) gives a value for α of 0.632 (significant at better than the 0.001% level) (see Table 2, column (1)).

The (quadratic) time trend Φ_t allows for aggregate variation over time in the rate at which unemployed workers are hired, and picks up exogenous shocks to the matching function common to all industries. Although it is only marginally significant, if the time trend is omitted the estimate of α is boosted to 0.800 (again significant at better than the 0.001% level) (column (2)).

Finally, imposing the constraint that matching efficiency is constant across industries, which enables estimation by OLS, reduces the estimated vacancy share to 0.522 (column (4)). However, this restriction is empirically invalid. (The Wald test statistic of $F_{17,732}$ =25.64 means that the joint hypothesis of equal fixed effects in column (1) is rejected at below the 0.001% level).

The value α = 0.632 is chosen for subsequent calculations. Correspondingly, the chosen estimates (discussed below) of matching efficiency by industry, ϕ_i, are also based on the specification in column (1).

This estimate of the vacancy share derived from comprehensive hiring, vacancy and unemployment data is reassuringly similar to previous UK estimates based on alternative data – and is also very similar to recent US findings (Sahin, Song, Topa and Violante, 2011; Borowczyk, Martins and Postel-Vinay, 2012). Sahin, Sopa, Tong and Violante (2010) choose a vacancy share estimate of 0.67 on the basis of British Claimant Count and JobCentre vacancy data disaggregated by occupation or occupation plus travel-to-work area.

Industry fixed effects ϕ_i measure each industry's matching efficiency. Table 3 lists these, ordered by the size of matching efficiency ϕ_i. The larger is the estimate of ϕ_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).[8]

There is substantial and perhaps encouraging correspondence between the industry matching efficiencies estimated here for the UK and those estimated for the US by Sahin, Song, Topa and Violante (2011). UK and US estimates both place Information and Finance close to the bottom of the

[7] 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 all tests (see Petrongolo and Pissarides, 2001, for a review of previous similar tests on the matching function).

[8] I follow standard practice and boldly interpret the fixed effects as reflecting relative matching efficiencies, but of course they will in fact capture all factors that are constant over time and specific to particular industries.

efficiency table, and the Arts and Construction industries near the top.[9] This ordering could reflect the fact that Information and Finance involve specialised skills, so the matching process takes longer. Construction, Water (and Sewage), Arts (Entertainment and Recreation) are industries requiring fairly general skills, so matching might be quicker on average. Some rankings probably reflect industry-specific hiring practices, including Education in the UK. As in the US, the high ranking of Construction probably reflects measurement error in vacancies, which are likely to be under-reported relative to other industries because of the prevalence of informal hiring practices.

6.2. The index of mismatch: The impact of mismatch on hiring

$\mathcal{M}_{\phi t}^{h}$, the key index of the extent of labour market mismatch across UK industries, is graphed in Figure 9. The numbers are the estimated fraction of actual hires 'lost' on account of mismatch. Hires would be boosted by that fraction if mismatch could be eliminated. During the 2000s, the UK operated at a 'normal' level of mismatch implying 3-4% lower hires than in the no-mismatch case (the case where the distribution of unemployment relative to vacancies across industries varies inversely perfectly with industry matching efficiency).

The start of the financial crisis saw a notable rise in mismatch: The fraction of hires lost rose for two years between 2008 and 2010, peaking at about 7%. However, mismatch seems to have corrected itself rapidly after that. By mid-2011, the fraction of hires lost was back down to a normal level close to 3%.

The cumulative number of hires lost due to mismatch during the financial crisis is estimated at 275,000. Although this might sound a low number, implying little effect from mismatch, it should be noted that this is the equivalent of a reduction in the *net* flows (since there is no counterbalancing flow). So the best scale against which to compare the number is probably the *net* inflow into employment. The hires lost due to mismatch are the equivalent of at least one whole year's net employment inflows. (Quarterly net flows UE minus EU averaged about 69,000 before the recession, and quarterly (UE+NE) minus (EU+EN) flows averaged 67,000. The relative impact of mismatch on hiring would be higher if compared against net employment inflows including the recessionary period, as these were substantially lower. Note that EE flows net to zero.)

6.3. The impact of mismatch on job finding

Figure 10 graphs the counterfactual outflow rate in the absence of mismatch, given by equation (23), and the actual outflow rate, f_t. The no-mismatch job finding rate, f_t^*, should capture all non-mismatch shocks.

The increase in mismatch between 2008 and 2010 discussed in Section 6.2 is apparent in the rapid decline in the actual job finding rate over this period. It is notable that the financial crisis does not seem to have been accompanied by any large non-mismatch shock: The non-mismatch outflow rate's path does not deviate much from a gentle downward trend. Since 2010, the actual outflow rate has recovered to a level consistent with a 'normal' amount of mismatch.

[9] Actual estimated coefficients are slightly higher for the US. Estimated match efficiencies UK/US are: Information 0.56/0.66; Finance 0.68/0.76; Arts 1.16/1.45; Construction 1.30/1.40. A full range of UK estimates are given in Table 1. US estimates come from Sahin, Song, Topa and Violante (2011, Table 3).

6.4. 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 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 ideas were outlined in Section 2.3. As equation (26) demonstrates, these shocks are captured, respectively, by the log change in the difference between steady state and no-mismatch steady state rates, and by the change in the log steady state no-mismatch unemployment rate.

Figure 11 plots these contributions to log steady state unemployment dynamics. Mismatch shocks explain more than half of the rise in the steady state unemployment rate during the 2008-09 recession. Post-recession, mismatch shocks (reductions) have tended to *reduce* steady state unemployment, so all increases in the steady state rate post-recession have reflected the contribution of other shocks.

A variance decomposition confirms that mismatch shocks played an unusually large part in steady state unemployment movements during the recession. Mismatch-related variation is estimated to explain 54% of steady state unemployment rate movements (see Table 4). Post-recession, the influence of mismatch relative to other shocks has declined back to a typical level.

Perhaps surprisingly, mismatch also appears to play a substantial part in changes in steady state unemployment in normal times, accounting for around 45% of movements. These findings echo those of Herz and van Rens (2011), who concluded – on the basis of US data across industries and across states – that “structural” (mismatch) and actual unemployment are equally cyclical.

This is confirmed in Figure 12, which plots the parts of the steady state unemployment rate attributable to mismatch and to other determinants alongside the overall steady state rate. There is substantial co-movement between the mismatch and non-mismatch components. One period of notable discrepancy is the 2008-09 recession, when the influence of mismatch on the steady state rate increased. The most recent data demonstrate that mismatch is not the prime driver of recent unemployment increases (and prior evidence in this paper indicates that inflow rates, rather than outflow rates, are largely responsible).

Findings concerning the 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 steady state rate – and, furthermore, the dynamics of actual unemployment depend on past steady state rates (summarising past shocks).

Key results for the UK differ from the US findings of Herz and van Rens (2011). Whereas they found that fluctuations in structural unemployment were small compared to the overall unemployment rate, Figures 11 and 12 suggest that “structural” fluctuations as measured in this paper can at times explain more than half of overall steady state unemployment movements.

6.5. Impact of mismatch on the actual unemployment rate

The dashed red line in Figure 13 plots the level of the fitted value of the actual unemployment rate that emerges from the non-steady state model. This fitted value reflects changes in both the steady state and in the dynamic path of unemployment that are affected by the changes in the overall job finding rate, and includes the effects of mismatch. The best picture of the overall contribution of mismatch to actual unemployment can be obtained by comparing this fitted value of the actual unemployment rate with the fitted value of the unemployment rate that would emerge in the absence of mismatch. The no-mismatch unemployment rate is also calculated using a non-steady state model, since it is also affected by the low UK transition rates that entail important turnover dynamics. The no-mismatch unemployment rate is calculated using the job finding rate estimated to prevail in the absence of mismatch, while the actual unemployment rate is calculated using the actual job finding rate.

Figure 13 shows that the pre-recession gap between actual and no-mismatch unemployment rates was around 1.2 percentage points in the early 2000s, rising to 1.7 percentage points just prior to the recession. During the recession this gap rose to around 2.5 percentage points, and since 2009 the gap has increased further, to roughly 3 percentage points.

An interesting aspect of Figure 13 is that the large divergence between actual and no-mismatch unemployment during the financial crisis only really begins 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 curves in Figures 6 and 7. During the recession, the fall in demand was accompanied by lower vacancy creation and a move south-east along what appears to be a stable Beveridge curve. It is only after the official recession ended that the Beveridge curve appears to shift upwards and outwards, consistent with increased mismatch. The two mismatch indicators in Figures 8 and 9 suggest that mismatch *did* worsen during the recession, but also continued to fall for about a year after the recession ended. The sclerotic nature of the UK labour market means that the 'lagged' response of actual unemployment to these changes in mismatch is not surprising: The persistent effect of shocks is apparent from the large contribution of the recursive components in Table 1.

In terms of contributions to the *dynamics* of actual unemployment, Figure 14 performs a similar analysis to that conducted for the steady state rate in Section 6.4. Evidence indicates that increases in mismatch contributed about half of overall movements in the actual unemployment rate during the financial crisis. Post-recession, the UK unemployment rate has been very static. The fact that the recent UK unemployment rise results from factors other than mismatch is evident in the latest data in Figure 14.

6.5.1. The role of innovation and recursive coefficients

Current and past changes in the steady state unemployment rate make up one component of actual unemployment rate dynamics. The other aspect to consider is the coefficients that determine how actual unemployment responds to current shocks that change current steady state unemployment rate and to past shocks affecting past steady state unemployment.

Figure 15 plots both innovation and recursive coefficients. Their actual value depends on the outflow rate, so it is possible to calculate what values these coefficients would take in the absence of mismatch. These no-mismatch coefficients are also plotted.

Increased mismatch reduces the innovation coefficient and temporarily reduces the recursive coefficient (which is then boosted as mismatch stabilises). Both innovation and recursive coefficients would (eventually) return to their prior values if mismatch were to do likewise. Figure 16 highlights the effects of the documented changes in mismatch by plotting the proportion by which the recursive and innovation coefficients are higher or lower as a result of mismatch.

7. Conclusion

The UK Beveridge curve paints a worse picture than the US curve. Vacancy creation in the UK has been weak. The vacancy rate has risen by less than 15% since the end of the recession in 2009, and the impact on unemployment of that vacancy creation has been non-existent. In contrast, the US vacancy rate has doubled, and US unemployment has fallen back to below the UK level, having been nearly two percentage points above the UK at the worst point. The failure of the UK unemployment rate to fall is undoubtedly at least in part due to weak demand, but it also raises the possibility of an increase in structural unemployment. This paper investigates whether the behaviour of unemployment is linked to mismatch. Has the financial crisis resulted in a pool of unemployed workers whose characteristics – in terms of skills, industry, occupation or location – do not match requirements of available job openings?

This paper ties together dynamic decompositions of actual unemployment developed by Elsby, Hobijn and Sahin (forthcoming) and Smith (2011) with measures of mismatch between unemployment and vacancies, drawing on the mismatch indices developed in Sahin, Song, Topa and Violante (2011). Accounting exercises are performed that lead to estimates of the extents to which actual and steady state UK unemployment have been raised due to mismatch, and estimates of the effects of mismatch on the dynamic path towards the steady state.

Results indicate that, overall, mismatch across industries has contributed around one half of the rise in UK (steady state and actual) unemployment during the financial crisis. The rise in mismatch led to up to 4% fewer hires per quarter. During the financial crisis, the cumulative total hires lost was around 275,000. This hires deficit arose because the unemployment outflow rate fell by over one fifth during the recession compared to the counterfactual outflow rate that would prevail in the absence of mismatch. The estimated loss in hires due to mismatch is equivalent to at least one year's worth of net employment inflows.

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Tables

	Outflow rate			Inflow rate	
			Total		
Contribution of innovations			*0.48*		
by flow rate	0.23			0.25	
Contribution of past shocks			*0.34*		
by flow rate	0.20			0.15	
Total contribution to actual *u* dynamics	0.42			0.40	
of which	Job finding rate	Outflow rate via non-participation		Separation rate	Inflow rate via non-participation
Total contribution to actual *u* dynamics	0.30	0.11		0.33	0.07
Contribution of innovations	0.15	0.07		0.19	0.06
Contribution of past shocks	0.15	0.04		0.14	0.01

Table 1. Contributions to actual log unemployment dynamics

Notes: Estimates are based on a non-steady state model, using QLFS micro data from 1992q2 to 2011q4. Rows and columns might not sum due to rounding.

	(1)	(2) No time trend	(3) Pre-2008q2	(4) OLS
α	0.632***	0.800***	0.750***	0.522***
	(0.0251)	(0.0213)	(0.0371)	(0.0181)
Fixed effects	yes	yes	yes	no
Quadratic time trend	yes	no	yes	yes
Seasonal dummies	yes	yes	yes	yes
R^2	0.720	0.762	0.752	0.686
Observations	756	756	486	756
Industries	18	18	18	18
Sample period	2001q3-20011q4	2001q3-20011q4	2001q3-2008q1	2001q3-20011q4

Table 2. Estimates of the vacancy share, α

*Notes: Standard errors in parentheses. *** indicates significance at the 1% level.*

Industry	ϕ_i
Construction	1.30
Water	1.18
Arts	1.16
Education	1.10
Public admin and defence	1.07
Real estate	0.96
Utilities	0.96
Health	0.92
Other services	0.92
Transport	0.82
Administration	0.80
Professional, technical	0.80
Mining	0.79
Manufacturing	0.76
Wholesale and retail	0.69
Finance	0.68
Accommodation	0.67
Information	0.56

Table 3. Industry-specific matching efficiencies, ϕ_i

Notes: Estimates are industry fixed effects from the panel regression reported in column (1) of Table 2.

		Mismatch	Non-mismatch
Recession	2008q2-2009q3	0.54	0.47
Post-recession	2009q4-2011q4	0.46	0.54
Pre-recession	2001q3-2008q1	0.44	0.57
Full sample	2001q3-2011q4	0.47	0.54

Table 4. Relative effects of mismatch and non-mismatch shocks on changes in the steady state unemployment rate

Notes: 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). Rows might not sum to unity due to rounding.

Figures

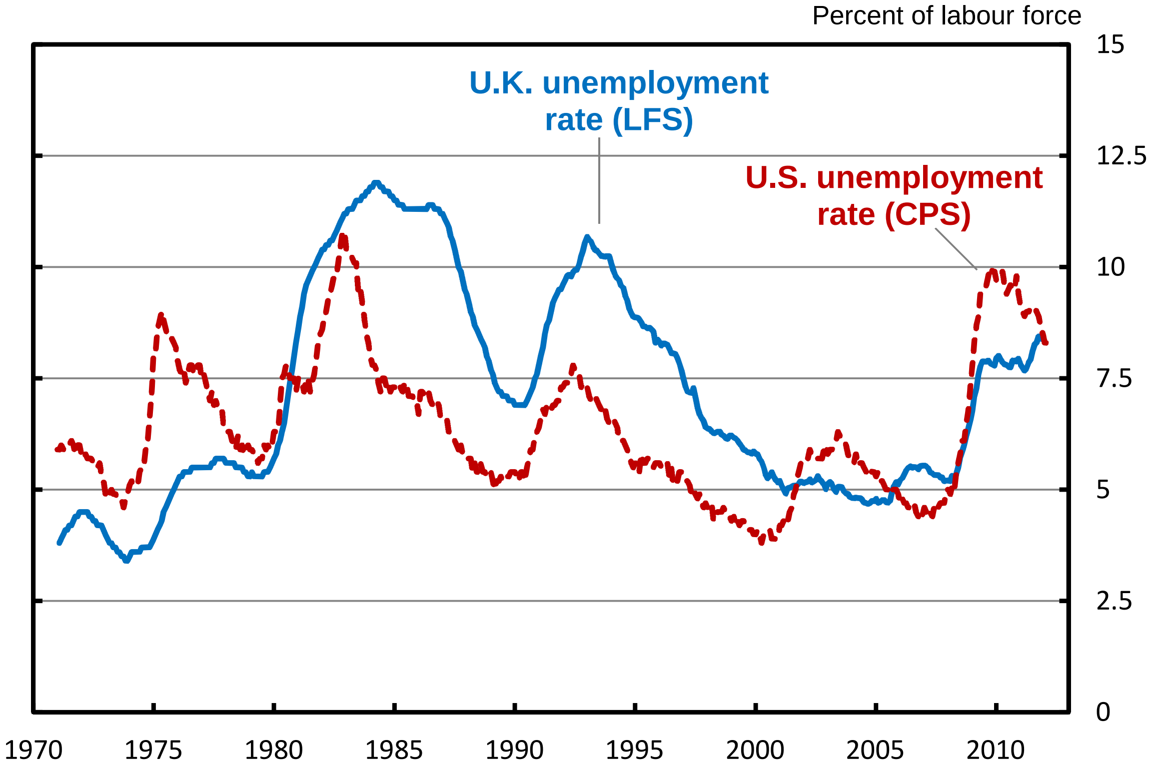

Figure 1. UK and US unemployment rates, 1970-2012

Ages 16 and over. Sources: ONS, BLS.

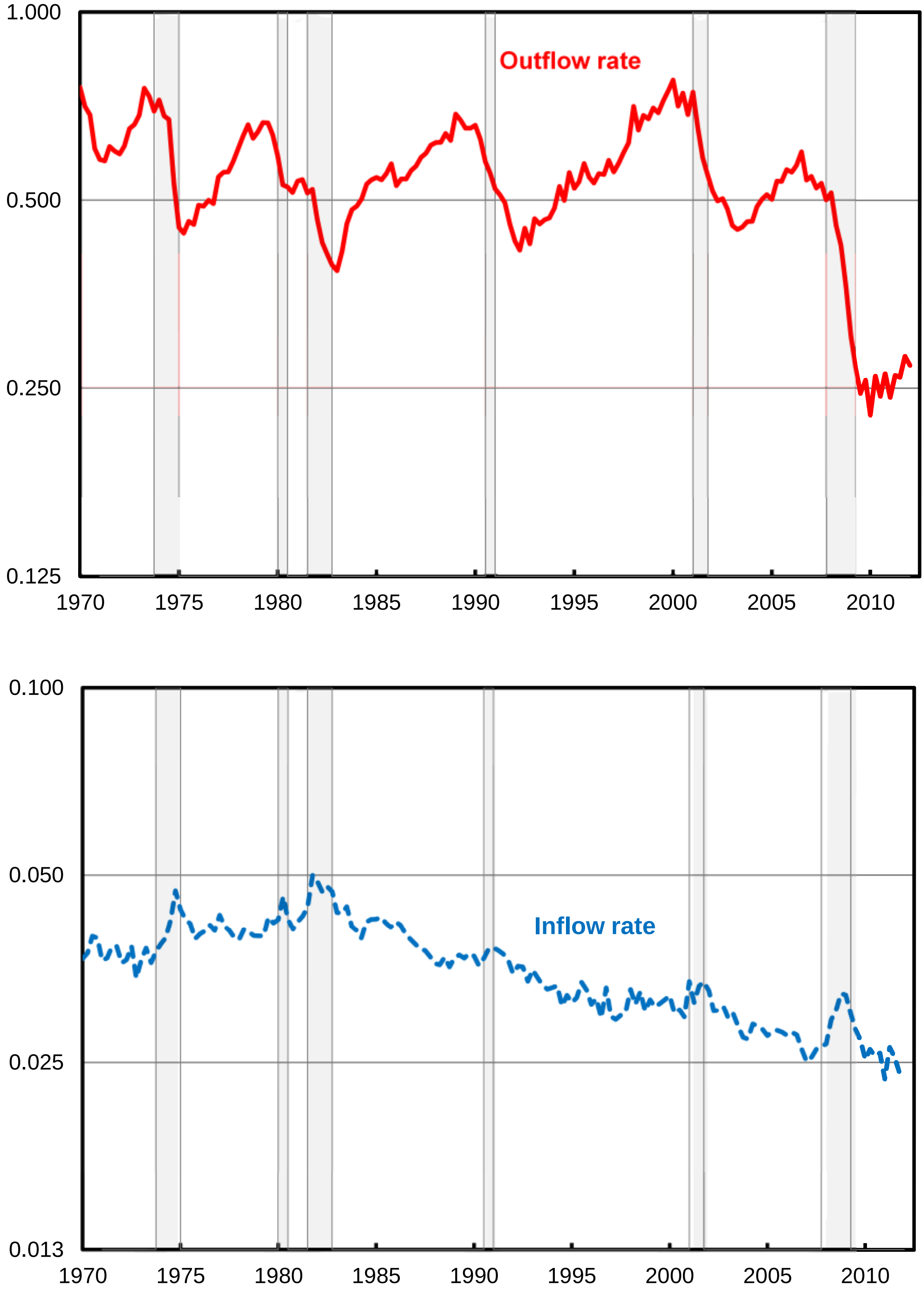

Figure 2. US unemployment outflow and inflow rates, 1970-2012

Source: Author's calculations using Shimer's (2012) method on BLS CPS duration data.

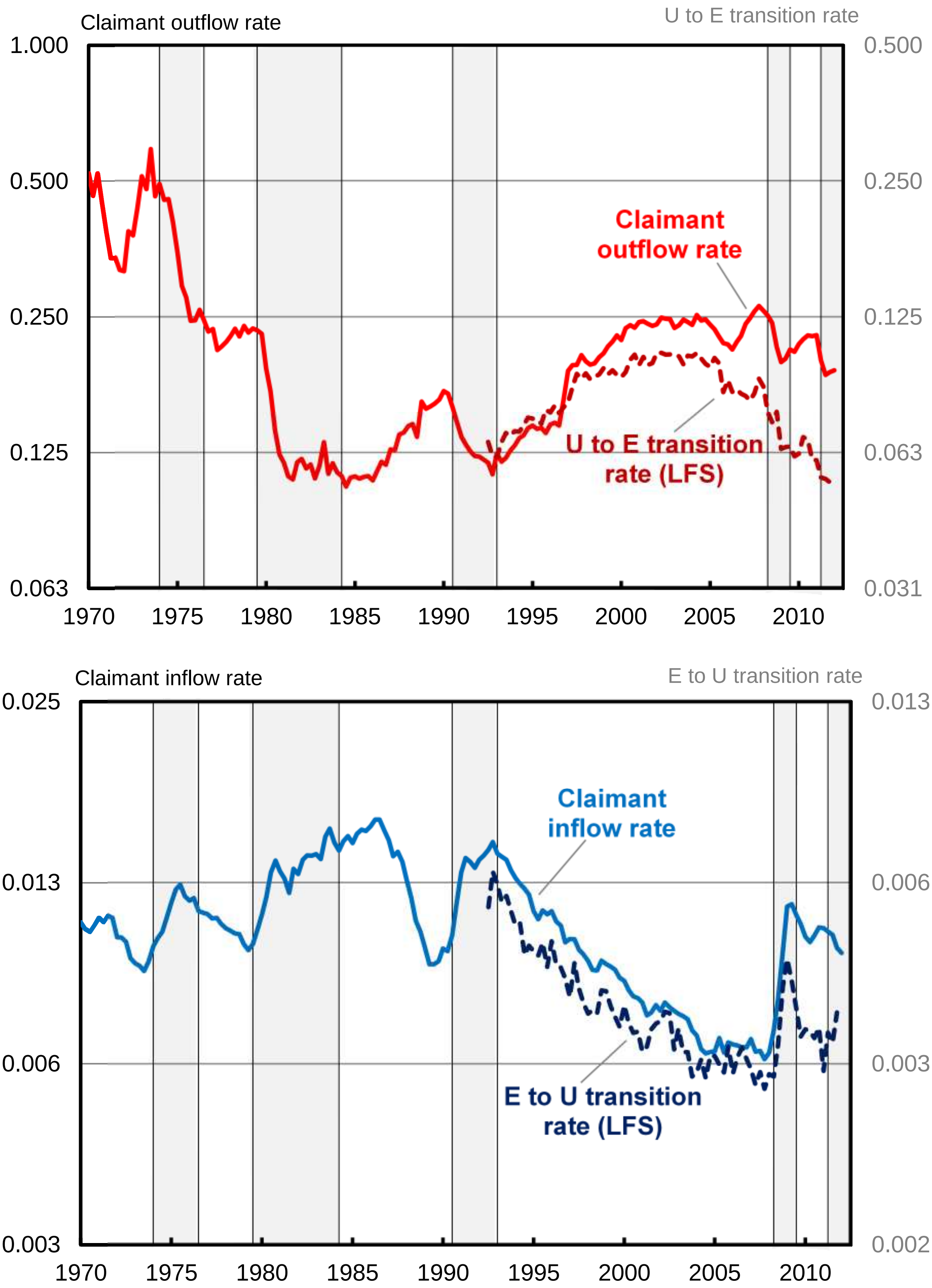

Figure 3. UK unemployment outflow and inflow rates, 1970-2012

Sources: Author's calculations using Shimer's (2012) method on ONS NOMIS Claimant Count data for Great Britain (data from Petrongolo and Pissarides, 2008, prior to 1983) and using LFS microdata.

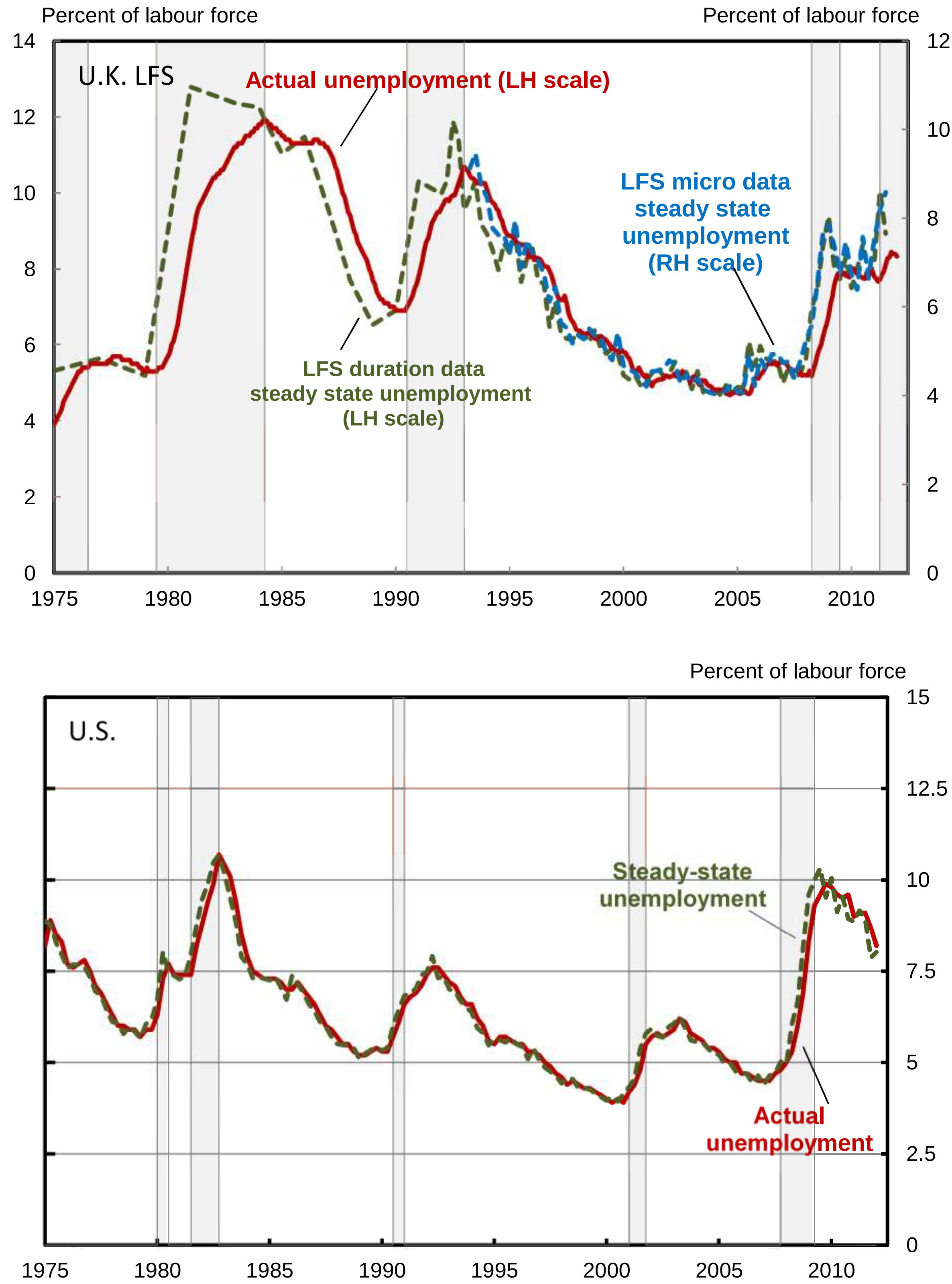

Figure 4. UK and US actual and steady-state unemployment rates, 1975-2012

Sources: UK: ONS LFS, author's calculations using Shimer's (2012) method based on LFS duration data, and LFS/QLFS micro data. US: BLS CPS and author's calculations using Shimer's (2012) method based on duration data.

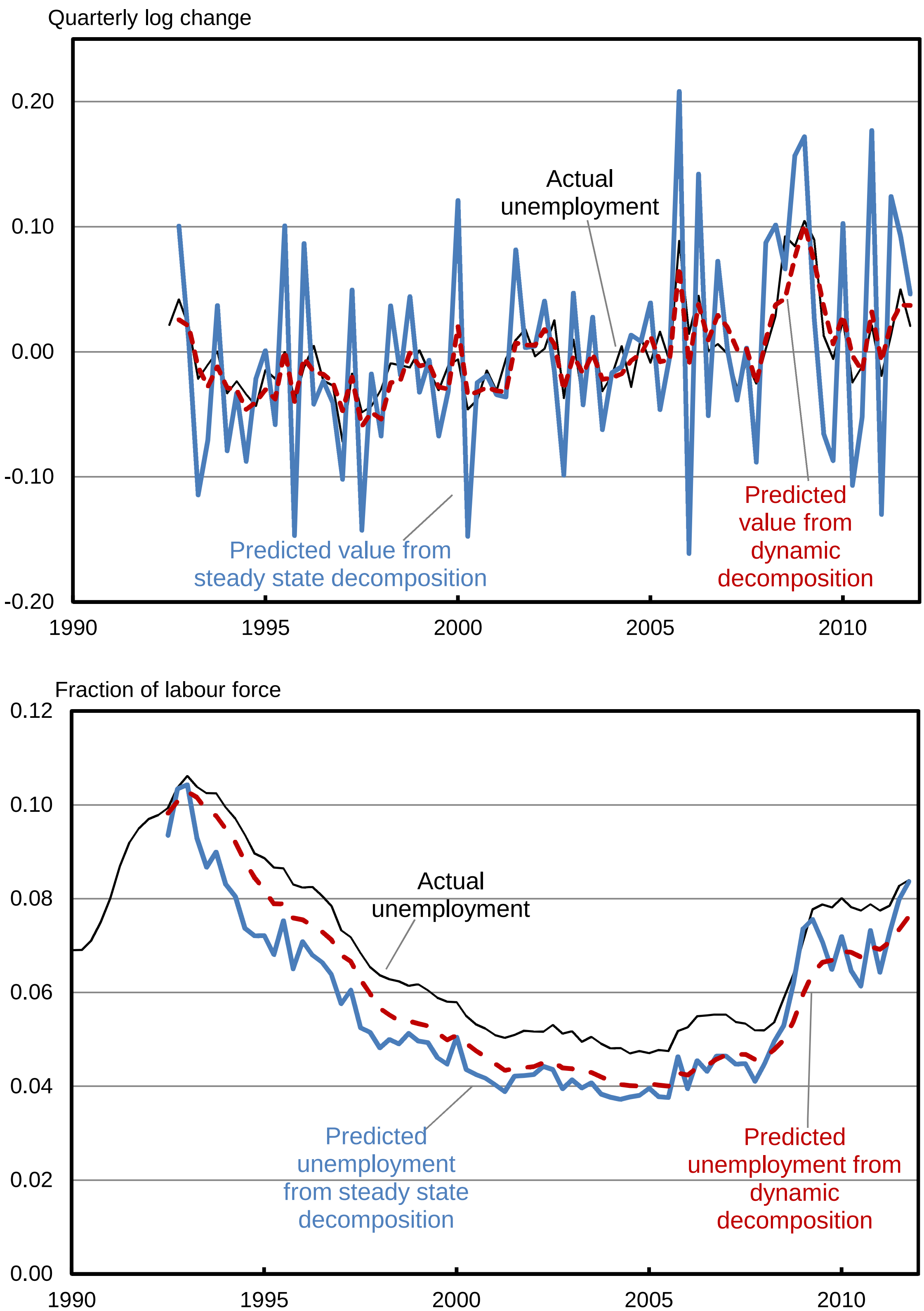

Figure 5. Actual UK unemployment rate and fitted values from non-steady state and steady state models of unemployment dynamics, 1992-2011

Sources: ONS and author's calculations using ONS QLFS micro data.

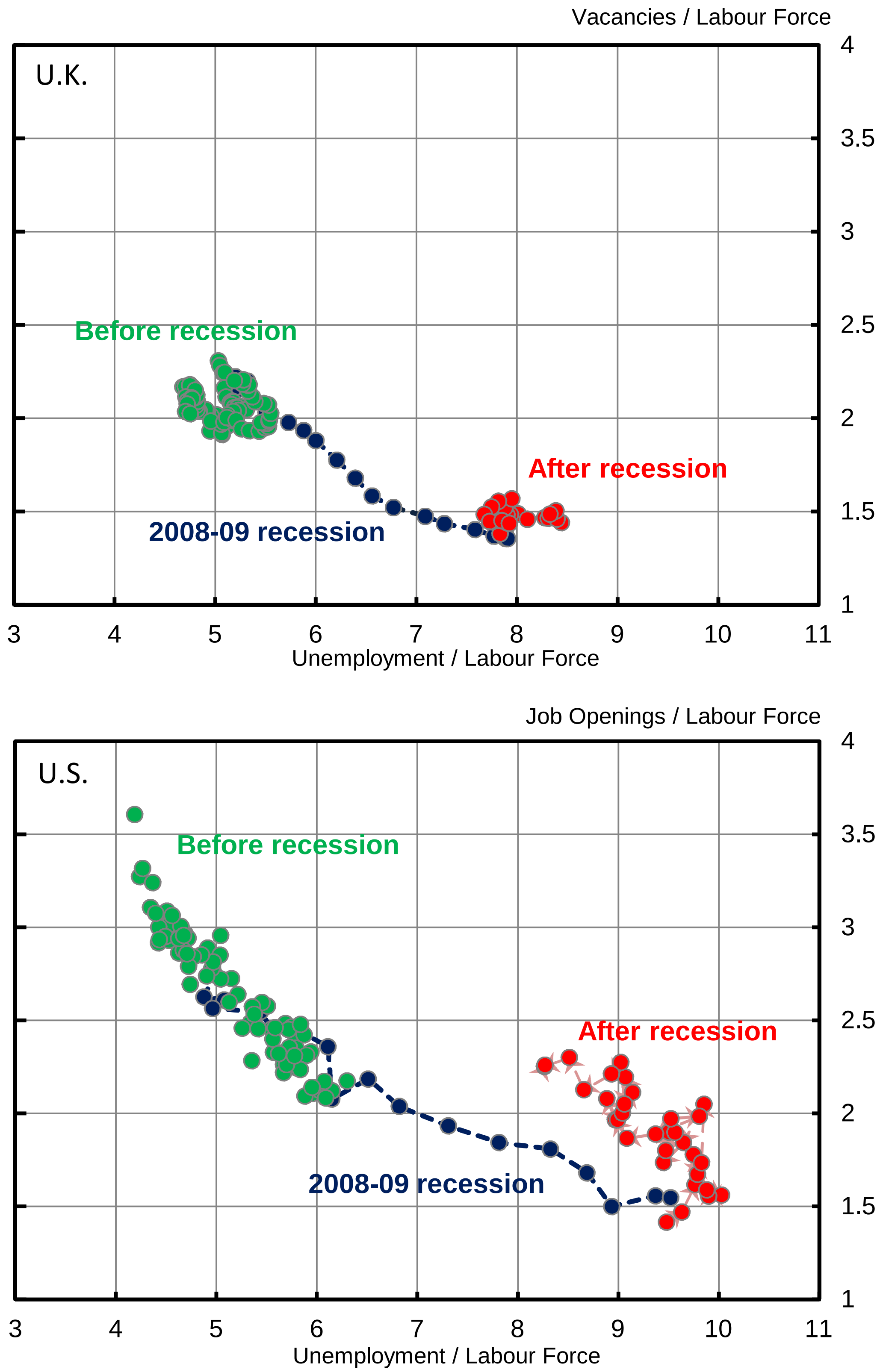

Figure 6. UK and US Beveridge Curves, 2001-2012

Sources: Author's calculations using ONS Vacancy Survey and LFS and BLS JOLTS and CPS. UK data span May 2001 to January 2012. US data cover January 2001 to February 2012.

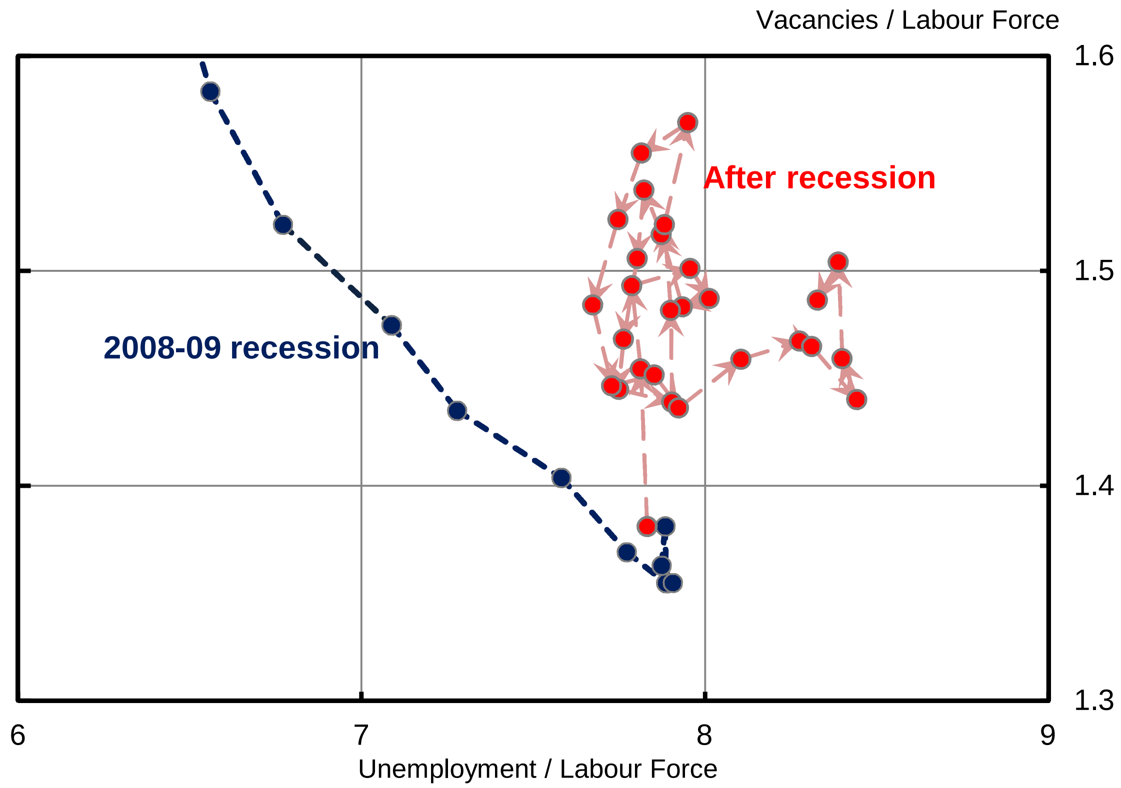

Figure 7. UK Beveridge Curve, 2008-2012

Sources: Author's calculations using ONS Vacancy Survey and LFS.

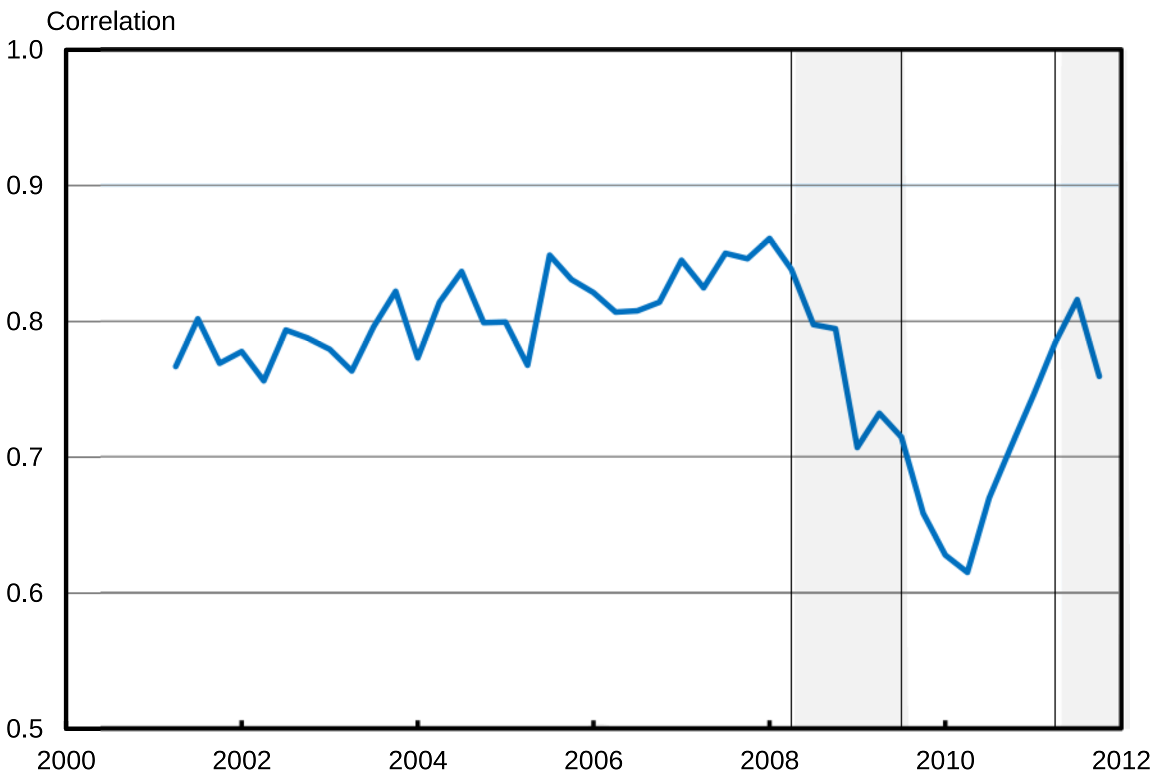

Figure 8. Correlation across industries between unemployment and vacancy shares, 2001q3-2011q4

Sources: Author's calculations using ONS Vacancy Survey and QLFS micro data. Correlation is taken across 18 industries (SIC 2007 Sections B to S).

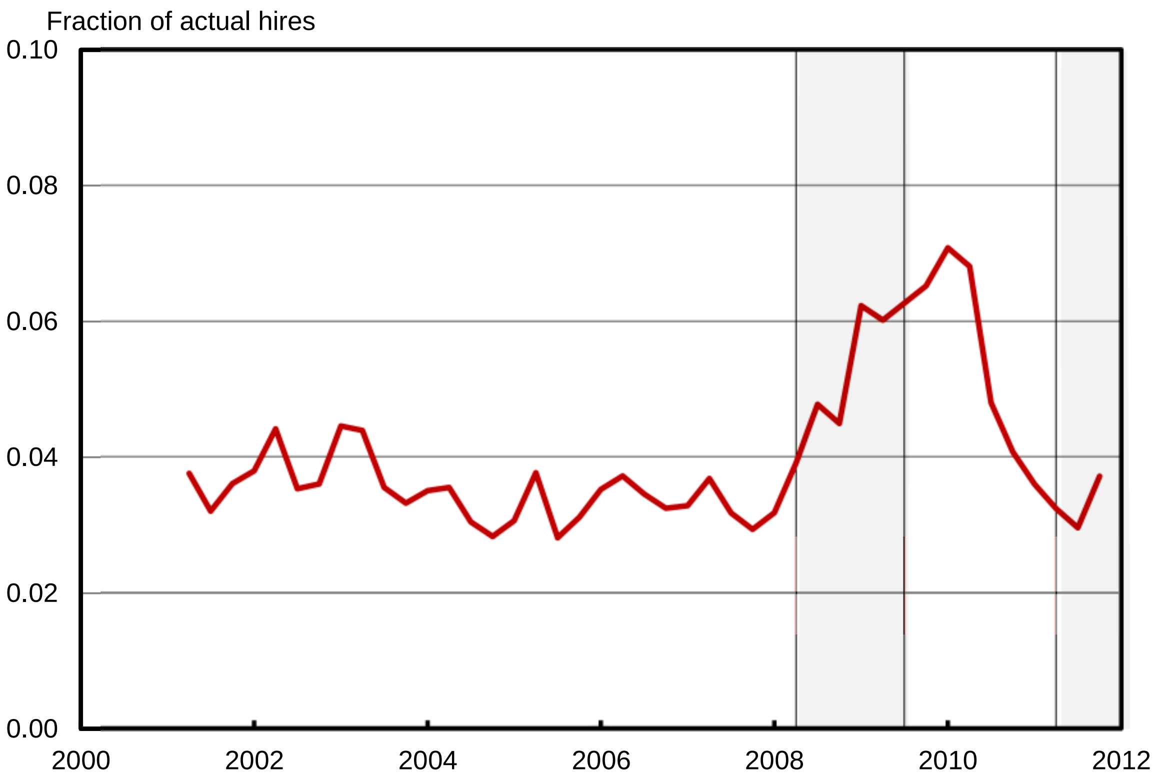

Figure 9. Hires deficit due to mismatch, 2001q3-2011q4

Sources: Author's calculations using ONS Vacancy Survey and QLFS micro data. Estimates are based on 18 industries (SIC 2007 Sections B to S) and on vacancy share and industry match efficiencies calculated using the full sample period (as reported in Table 2, column (1) and Table 4).

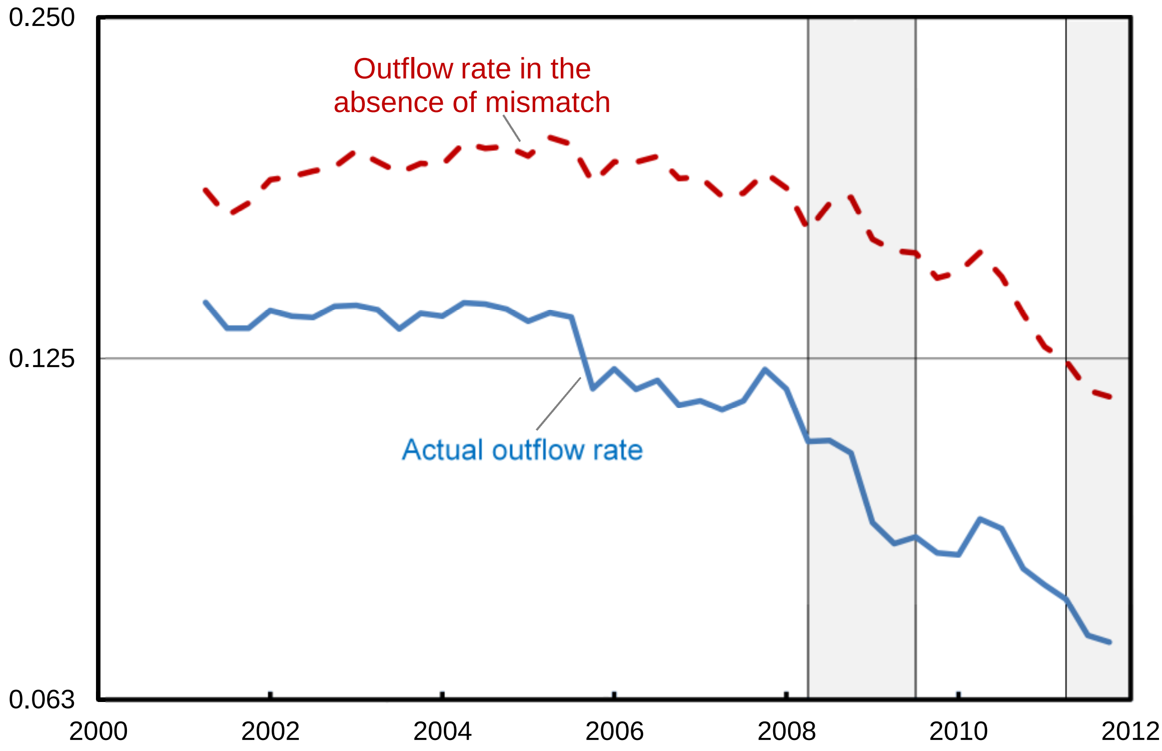

Figure 10. Actual monthly unemployment outflow rate and the counterfactual outflow rate in the absence of mismatch, 2001q3-2011q4

Sources: Author's calculations using ONS Vacancy Survey and QLFS micro data. Flow rates are plotted on a logarithmic scale.

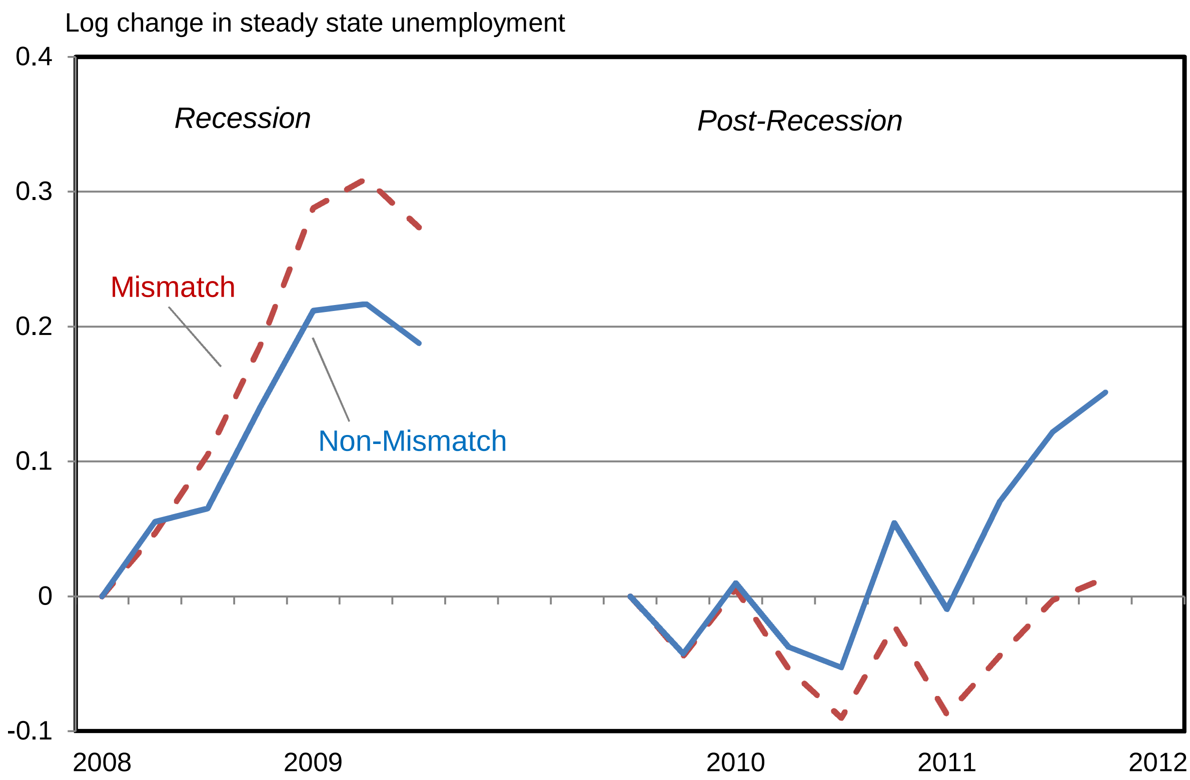

Figure 11. Contributions of mismatch and non-mismatch shocks to steady state unemployment dynamics

Sources: Author's calculations using QLFS micro data and ONS Vacancy Survey and QLFS micro data. The graph plots cumulative log changes in components of the steady state unemployment rate. "Recession" denotes 2008q1-2009q3. "Post-recession" is 2009q3-2011q4.

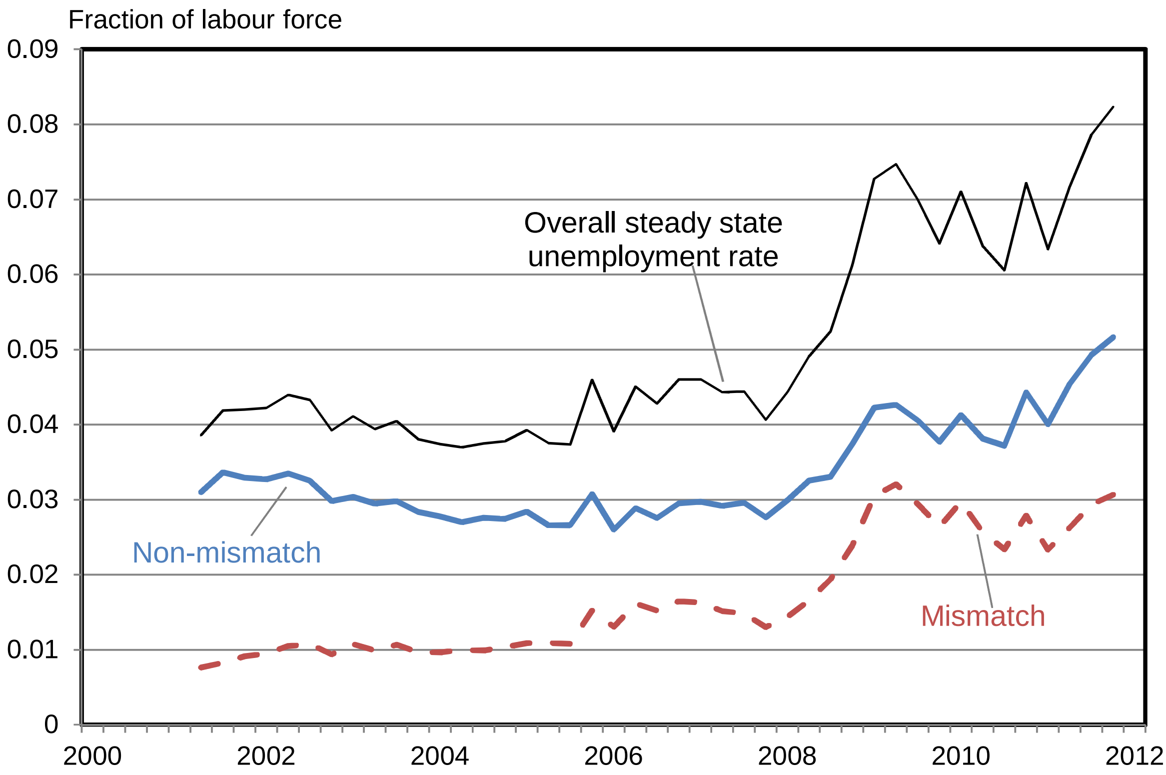

Figure 12. Steady state unemployment rate and parts due to mismatch and to other factors

Sources: Author's calculations using QLFS micro data and ONS Vacancy Survey and QLFS micro data.

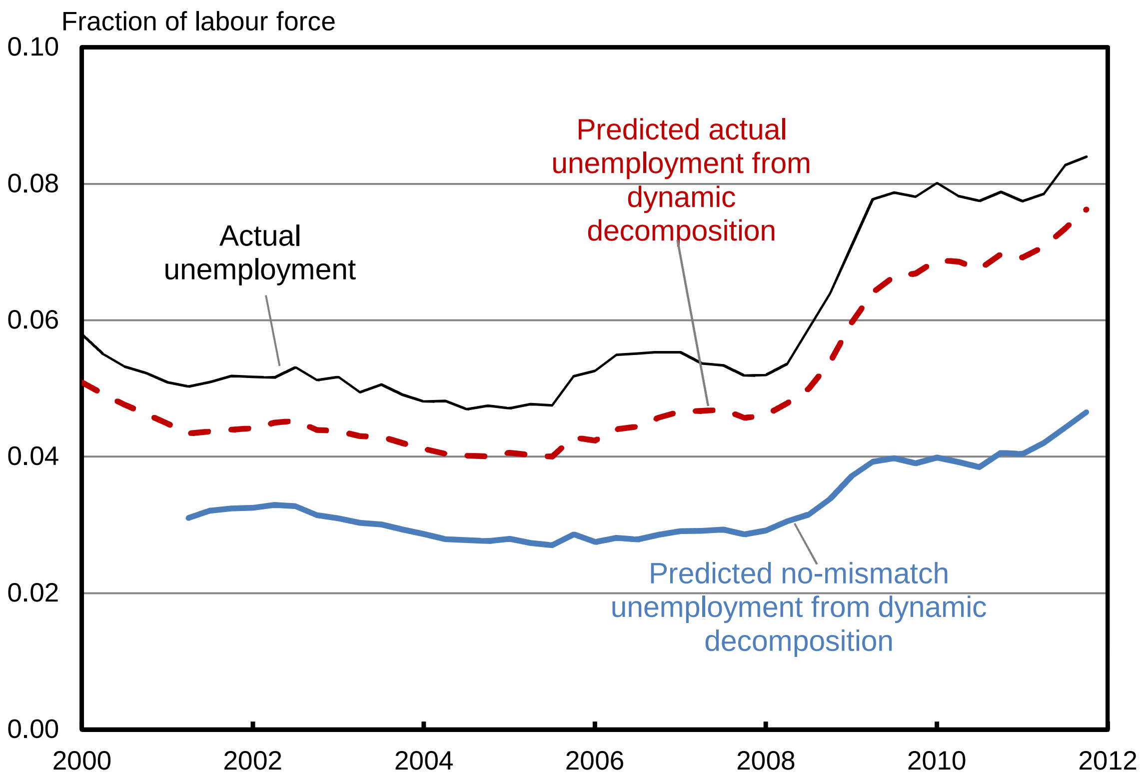

Figure 13. Actual unemployment rate and predicted unemployment rate in the absence of mismatch, 2000q1-2011q4

Sources: Author's calculations using QLFS micro data. Due to availability of vacancy data, estimates of unemployment in the absence of mismatch can only be constructed from 2001q3.

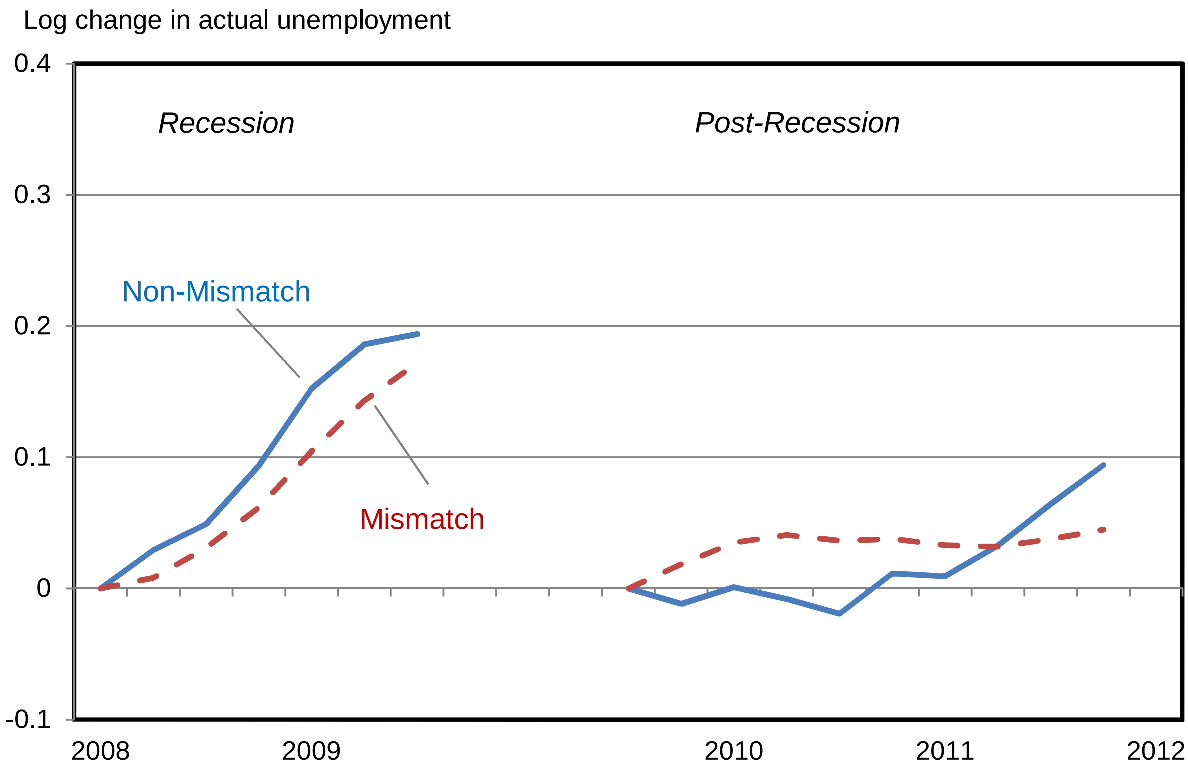

Figure 14. Contributions of mismatch and non-mismatch shocks to actual unemployment dynamics

Sources: Author's calculations using ONS Vacancy Survey and QLFS micro data. The graph plots cumulative log changes in components of the fitted actual unemployment rate based on a non-steady state model. "Recession" denotes 2008q1-2009q3. "Post-recession" is 2009q3-2011q4.

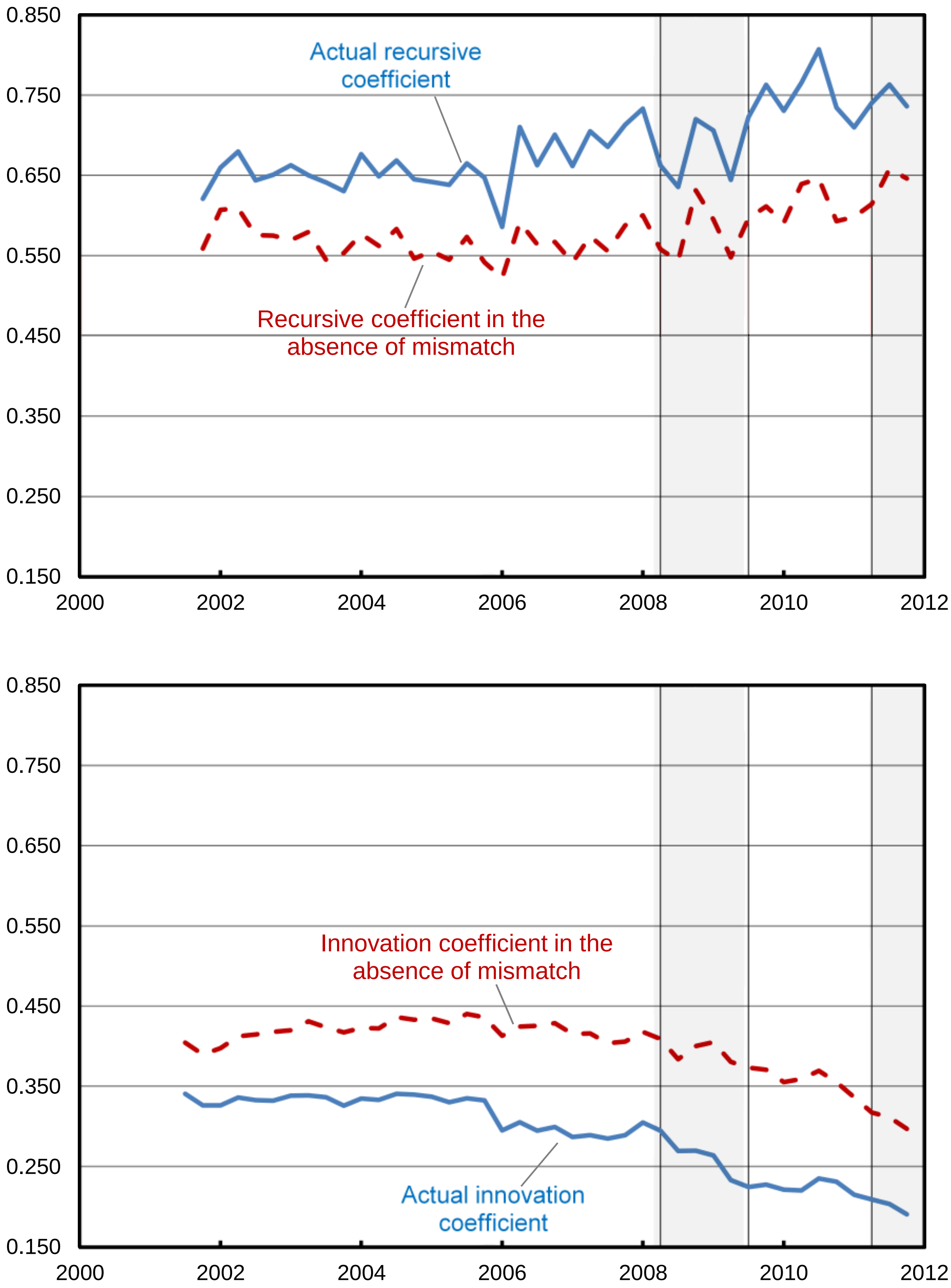

Figure 15. Upper panel: Actual coefficient for past flow rate shocks on current unemployment and the counterfactual coefficient in the absence of mismatch, 2001q3-2011q4.
Lower panel: Actual impact coefficient of current flow rate shocks on current unemployment and the counterfactual impact in the absence of mismatch, 2001q3-2011q4.

Sources: Author's calculations using ONS Vacancy Survey and QLFS micro data.

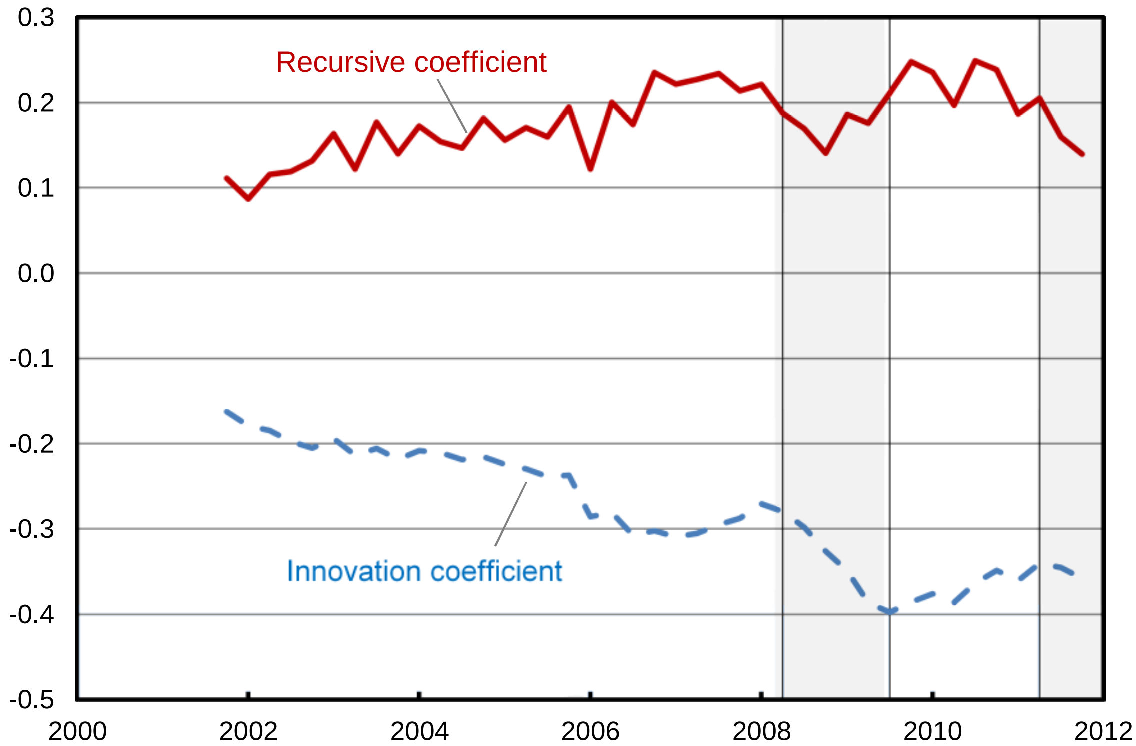

Figure 16. Difference between actual data and no-mismatch counterfactual, as a proportion of actual data, in the impacts of current and past flow rate shocks on current unemployment, 2001q3-2011q4.

Sources: Author's calculations using ONS Vacancy Survey and QLFS micro data.

Appendix

Data

This paper is upfront about using fairly aggregated data to measure mismatch. Any index of the degree of mismatch will tend to vary inversely with the level of aggregation. There are a number of reasons this paper prefers to use higher-aggregation data. The first is simply data availability, particularly in relation to comprehensive UK vacancy data. Related to this is the problem of measurement error, which increases with disaggregation. But at least as important is the suspicion that shocks that impact importantly on mismatch typically occur at a fairly aggregated level.

Unemployment by industry: the Labour Force Survey

I construct data on unemployment by previous industry of employment using quarterly Labour force Survey (QLFS) micro data. The LFS is a quarterly survey of a representative sample of UK households. Around 41,000 households comprising 103,000 individuals are surveyed. Households remain in the sample for five quarters, unless they move address, with one fifth of the sample replaced each quarter.

Data on unemployment aggregated by previous industry of employment is also published by the UK Office for National Statistics (ONS) (in release UNEM03) and can be used to check micro data estimates.

One complicating factor is a change of industry classification from Standard Industrial Classification (SIC) 2003 to SIC 2007, which was implemented at the beginning of 2009. 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. Thus, like the ONS LFS themselves, I treat SIC 1992 and SIC 2003 classifications as identical. For each relevant individual in the survey between the fourth quarter of 1983 and the fourth quarter of 2008, inclusive, I have reclassified their industry of current and previous employment from the SIC 1992/2003 classification to SIC 2007. The mapping was performed by allocating each SIC 1992/2003 Industry Class (the 4-digit level, with around 460 categories) to a SIC 2007 Industry Section (essentially a 1-digit level, involving 21 categories). I am very grateful to Sean Milburn of the LFS Research team in ONS Social Survey Division for providing the coding used for the mapping. 18 Industry Sections are used in this paper. I exclude Agriculture, Household employers, and Extra-territorial organisations, for which there are no ONS Vacancy Survey data available.

Vacancies by industry: the ONS Vacancy Survey

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.

The Vacancy Survey's single question, asked at enterprise level, is "How many job vacancies did your business or organisation have on [*the reference date*] for which you were actively seeking recruits from outside your business or organisation?" The reference date is the Friday between the 2nd and the 8th of the month. Almost all responses are typed by telephone keypad (only 1% respond by surface mail).

The sample size is about 6,000, representative of UK enterprises. 1,300 large enterprises are surveyed each month, and the remaining 4,700 are smaller enterprises randomly sampled on a quarterly basis. Typically the Head Office of the business responds, but for some large organisations with multiple sites, data are collected at the local level. The survey achieves a response rate in excess of 80%.

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. See http://www.ons.gov.uk/ons/rel/lms/labour-market-trends--discontinued-/volume-111--no--7/the-vacancy-survey--a-new-series-of-national-statistics.pdf or http://www.ons.gov.uk/ons/guide-method/method-quality/quality/reviews/triennial-review-of-the-vacancy-survey-2012.pdf for further details.

A vacancy is defined in the Vacancy Survey as a position that: is newly created and/or unoccupied, or identified as becoming vacant in the near future; the employer has taken active steps to fill, and is prepared to take more steps; is available for a suitable candidate, and open to people from outside the business or organisation, either immediately or in the near future after the necessary recruitment procedure. "Active steps to fill the position" include advertising the vacancy in the media or on a public notice board, or registering with a Jobcentre or private employment agency. It should also involve approaching, interviewing or selecting potential recruits.

Enterprises are asked to include:

- Vacancies for currently occupied posts for which they have already been taking active steps to seek a replacement, for example as a result of retirement, resignation, promotion.
- Vacancies for both full-time and part-time posts.
- Vacancies for both permanent and fixed-term posts.
- Vacancies for casual staff employed to cover temporary absences, for example maternity leave, long-term sickness.
- Vacancies with a long recruitment process, for example graduate recruitment.
- Vacancies for newly created posts.

Enterprises are advised to exclude:

- Temporary absences where they intend leaving the post empty, that is, where employees will be returning from paid or unpaid leave.
- Vacancies due to reorganisation within the business/organisation, that is, if the vacancy does not become open to external applicants.
- Unpaid or voluntary jobs.
- Vacancies for which a job offer has already been accepted.
- Vacancies for work to be undertaken by subcontractors, for example consultants.
- Vacancies for positions outside the UK.

Vacancies are classified by industry according to the Inter-Departmental Business Register's (IDBR) record of the main industry of the enterprise.

Hires by industry and by skill: the Labour Force Survey

Data on hires are scarce in the UK. Previous work has tended to rely on data related to the unemployed who claim benefit – data which relate the number and flows of Claimants to vacancies posted at JobCentres (the UK employment service). From this source, measures of hires are available either based on Claimant outflows or Vacancy outflows.

In this paper, a measure of hires is constructed that is equivalent to that available from JOLTS (the Job Openings and Labor Turnover Survey of establishments in the US). In JOLTS, monthly hires are defined as *all* additions to the payroll during the reference month. This includes:

- Newly hired and rehired employees.
- Permanent, short-term, and seasonal employees.
- Full-time and part-time employees.
- On-call or intermittent employees who returned to work after having been formally separated.
- Workers who were hired and separated during the month.
- Transfers from other locations.
- Employees recalled to a job following a formal layoff lasting more than 7 days.

Establishments are asked to exclude:

- Transfers or promotions within the sampled establishment.
- Employees returning from strikes.
- Employees of temporary help agencies, employee leasing companies, outside contractors, or consultants.

I calculate hires using QLFS data by an industry as all inflows into an industry from employment in a different firm, from unemployment and from nonparticipation. In all cases, hires are defined in terms of hiring (destination) industry, and encompass all originating industries.

Robustness of results

Change in industry classification

The robustness of results can be checked in relation to different mappings from the 1983-2008 raw QLFS data's industry classification SIC 1992/2003 to the consistent classification used in this paper, SIC 2007, which applies post-2009 in QLFS and also applies to ONS Vacancy Survey data (the publicly released pre-2009 Vacancy Survey data having been mapped from SIC 1992 by the ONS using a mapping matrix based on the Inter-Departmental Business Register (IDBR)). The LFS mapping differs somewhat from the IDBR mapping. The IDBR mapping is available in spreadsheet form (by proportions and at 2-, 3-, and 4-digit level) on the ONS website. Although the mappings result in somewhat different unemployment stocks by industry after 2009, the results in this paper are similar whichever mapping is used. It should be noted that the mapping is not the only potential problem resulting from the SIC classification change in 2009. At that time a 'coding tool' was introduced, which is an algorithm to allocate verbal responses concerning current or previous industry to a SIC 2007 category. An ONS report to the LFS Steering Group suggests that anomalies in the coding might have resulted in possible inconsistencies in time series.

Different measures of hires

The measure of hires preferred for the main results in the text was chosen partly for its comprehensive nature and partly because it represents the best mirror of the JOLTS hires data commonly used. However, other measures can also recommend themselves conceptually. There are two factors that particularly need to be borne in mind. It is important to consider what assumptions it is reasonable to make about search behaviour, and which data best accord with these. Data availability also plays a part in the measures typically chosen. The theoretical model behind he mismatch measures used here assumes that only unemployed workers search (entailing no on-the-job search by current employees, and no search by those who classify themselves as inactive). However, the hires measure typically used in prior US work on mismatch, from JOLTS, involves total hires, so in practice does include hires from employment and from nonparticipation.

Table A1 reports results for the vacancy share α from estimating the matching function (27) (assuming it has Cobb Douglas form with constant returns to scale) for different measures of hires, and reveals markedly different results, which might be worth investigating in future work.

	Hires measure	α	s.e.	R^2
(1)	Total hires	0.632***	(0.0251)	0.720
(2)	Hires from *U* or *N*	0.431***	(0.0337)	0.452
(3)	Hires from *U*	0.285***	(0.0405)	0.279
(4)	Hires from *N*	0.542***	(0.0407)	0.540
(5)	Hires from *E*	0.701***	(0.0262)	0.745
(6)	Hires from *U* or *N*, by previous industry	0.291***	(0.0341)	0.406
(7)	Hires from *U*, by previous industry (here, *H/U* is the job finding rate)	0.152***	(0.0376)	0.241
(8)	Hires from *N*, by previous industry	0.525***	(0.0418)	0.517

Table A1. Effect of different hiring measures on estimates of the vacancy share, α

*Notes: Sample period is 2001q3-2011q4. All regressions include industry fixed effects, a quadratic time trend and seasonal dummies. Standard errors in parentheses. *** indicates significance at the 1% level.*

Correction to unemployment stocks

For simplicity, it is sometimes assumed that unemployed workers search only in the industry from which they were made redundant. If this can be assumed, it will not matter whether the industry is measured as the industry of the worker's previous job, or the industry into which they are hired. Stocks of unemployment can, practically, only be measured by industry of previous employment. But hires can be measured by either industry of previous employment or hiring industry. There is a conceptual discrepancy in calculating the hiring rate as the ratio of hires by hiring industry to unemployment by previous industry (as is done in the main text). It would be possible to make an adjustment to counteract the fact that the unemployment stock is measured in terms of previous industry, rather than destination industry like the other two key variables. Measuring unemployment by destination industry is theoretically desirable in that it is a measure of excess labour supply in the industry where the unemployed worker is searching. Sahin, Song, Topa and Violante (2011, Appendix A2) show that it is possible to correct the measured unemployment stock by previous industry, to the extent that this overstates the true variable of interest – unemployment with respect to destination industry – as a result of a time-varying factor that is common to all industries. This adjustment factor thus allows the job finding probability to be lower in all other industries (by a common factor) compared to the job finding probability in the industry of previous employment. This adjustment would make use of data on hires out of unemployment by previous industry and by current industry, which can be calculated from the QLFS. However, Sahin, Song, Topa and Violante (2011)'s results indicate that when calculated using CPS data, such an adjustment factor takes values close to unity. They find that the adjustment reduces the estimated level of mismatch, but makes little difference to the estimated impact of mismatch on the unemployment rate (essentially because this relies on mismatch dynamics), and it is not currently pursued in the present paper.

Different choices of α

Main results rely on a choice of 0.623 for α , the elasticity of the hiring rate to labour market tightness that seems recommended on the basis of the preferred hiring measure and in the light of results using several different specifications. It is of interest to investigate how robust are mismatch measures to the choice of α . Initial indications are that the higher is α , the lower is estimated mismatch (for given ϕ_i).

Different sample period

At present the estimates in the paper derived from the matching function are based on the whole sample period. An alternative would be to curtail the sample prior to the recession. The aim would be to use estimates of α and ϕ_i unaffected by any instability related to recession (which could bias the estimates).

Extensions and limitations

- The model on which the mismatch indices are based incorporates three labour force states. Future work could more explicitly elucidate the theoretical links between these and the empirical data.
- The analysis has assumed exogenous vacancy creation, which is clearly not valid. It would be useful to try to extend the work to incorporate endogenous job creation.
- It would be possible to extend the analysis to occupation, skill and region level. This would entail using JobCentre vacancy data. If shifts in vacancy levels due to employment agency practices can be overcome, these data could be combined with the LFS to give mismatch indices back to the late 190s (which would involve further mappings between SIC or SOC classification changes in LFS data).
- In a future version, the dominant role of the construction industry could be investigated.fs