University *of* Leicester

Department of Economics

Asymmetric volatility spillovers between UK regional worker flows and vacancies

Deborah Gefang, University of Leicester, UK

Geraint Johnes, Lancaster University, UK

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Deborah Gefang
Department of Economics
University of Leicester
Leicester LE1 7RH
United Kingdom

Geraint Johnes
Department of Economics
Lancaster University Management School
Lancaster LA1 4YX
United Kingdom

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Abstract

This paper investigates volatility spillovers between UK regional job finding, job separation and vacancy rates. Employing a logistic smooth transition vector autoregression (VAR) to model the large nonlinear dynamic system, we use the methods of Diebold and Yilmaz (2012) to decompose the forecast error variances. Our approach is Bayesian. More specifically, we extend doubly adaptive elastic-net Lasso (DAELasso) methods for VAR parameter shrinkage into a nonlinear framework to allow for the possible regime changes. We find that for each variable, both the volatility spillovers to and from other variables are high, providing clear evidence for the close interdependence between UK regional labour markets. The pivotal role of London in generating and spreading changes in volatility is highlighted. Analysis of net spillovers shows that, in general, shocks to job separation rates tend to spread into job finding and vacancy rates. By contrast, vacancy rates are usually at the receiving ends of shocks transmitted from the job separation and finding rates. We further examine the shock propagation mechanism in more detail, such as the differences in spillovers between regions within the same regime, and that of the same region but in different regimes. Finally, we draw inferences that are of economic and policy importance.

JEL: C11, C32, C51, J63.

1 Introduction

Recent years have witnessed a growing interest in empirically investigating the worker reallocation process within the standard Diamond - Mortensen - Pissarides search and matching framework (Diamond, 1982; Mortensen and Pissarides, 1994; Pissarides, 1985, 2000). Most of the studies use descriptive measures to capture the important features of the flows into and out of unemployment, and hence evaluate how the changes in flow rates affect the changes in unemployment rate (Hall, 2005; Fujita and Ramey, 2006, 2009; Shimer, 2007; Elsby *et al.*, 2009). More recently, noting that descriptive measures are unable to account for the labour market response to various shocks to the system, researchers have turned to VARs to examine the dynamics of workers' job seeking (and employers' recruiting) processes.

Among these, Fujita (2011) uses a structured trivariate vector autoregression (VAR) model consisting of inflow, outflow and vacancy rates to evaluate whether the job separation or job finding rate plays the dominant role in the dynamics of US labour market.[1] Given that the mechanisms underlying the job search/matching process can vary over time, Campolieti *et al.* (2012) extend the research of Fujita (2011) by using time-varying parameter vector autoregressions (TVPVAR) for data from North America (the USA and Canada) and Europe (France, Spain and the UK). Instead of focusing on the interrelationship between inflow, outflow and vacancy rates, Canova *et al.* (2012) look into how inflow, outflow, and unemployment rates react to technology shocks in a six-variable VAR model that consists of in-

[1] In this paper, we use inflow rate and separation rate interchangeably, outflow and job finding rate interchangeably

flows, outflows, vacancies, price for new equipment, labour productivity and hours. These studies using VAR models for the labour market all focus on aggregate data at national level. As a result, their findings can overlook important nuances, and even be misleading, when the job creation and destruction process at regional level is more of a concern.[2]

The interregional transmission of labour market shocks is an important issue for a number of reasons. If such transmission is slow, then the pace of economic growth will typically differ across space, and in extreme cases this can mean that macroeconomic policies that are well suited to one part of the country may not serve other parts so well. In the UK, there is currently some concern that the transmission mechanism that has, in the past, ensured that growth in leading regions trickles down to other areas, is either no longer working well or is working much more slowly as the economy recovers from the Great Recession (Townsend and Champion, 2014). This, then, is an appropriate time to re-investigate the mechanisms, using newly developed methods that allow more detailed analysis of the nature of transmission than was heretofore possible.

This paper focuses on the complex interrelationships between unemployment inflow, outflow and vacancy rates of 11 UK regions. Altogether, we have 33 variables that might be all interrelated. In order to avoid imposing 'incredible' restrictions in the sense of Sims (1972, 1980), we use an unrestricted VAR to model the complicated interlinkages between thirty-three endogenous variables. This sets the paper apart from the available stud-

[2]Papers such as Garrett (2003), Abadir and Talmain (2002), Forni and Lippi (1997, 99) show that the statistical properties of aggregate data can be very different from that of their disaggregate components.

ies such as Burda and Profit (1996) and Burgess and Profit (2001), which use single equation models or VARs of much smaller size. In addition, to account for the possible nonlinear effect in the interactions between VAR variables, we assume the regime changes are governed by a logistic smooth transition function (Maddala, 1977; Teräsvirta, 1994). Our estimation approach is Bayesian. Papers such as Banbura *et al.* (2010), Koop (2011) and Gefang (2014) show that large Bayesian VARs provide better forecasts and more sensible impulse response analysis than their non-Bayesian counterparts. Popular shrinkage methods for large Bayesian VARs include the traditional Minnesota prior of Doan *et al.* (1984) and Litterman (1986) and its natural variants (Kadiyala and Karlsson, 1997; Banbura *et al.*, 2010), the stochastic search variable selection (SSVS) prior of George *et al.* (2008), and the family of SSVS plus Minnesota priors of Koop (2011). Recently, Gefang (2014) introduces doubly adaptive elastic-net Lasso (DAELasso) for VAR shrinkage. Compared to other Bayesian VAR methods, DAELasso is more data based. In this paper, we use DAELasso for VAR parameter shrinkage so as to let the data speak.

We use the generalized spillover measure (GSM) of Diebold and Yilmaz (2012) to investigate the shocks propagating mechanism between variables and regions. GSM is currently among the most popular tools for investigating spillover effects using VAR models (Antonakakis, 2012; Altera and Beyer, 2014) . GSM does not require orthogonal innovations to decompose the forecast error variances, which is especially desirable when there is a lack of theoretical guidance on identifying the structure of a complex dynamic system. Various structured VAR models are used in the literature on the labour market. Papers such as Braun *et al.* (2007) and Canova *et al.* (2012) assess the effect of different types of shocks to the labour market by including variables such as productivity and hours into the system. Fujita (2011), however, shows that labour market reallocation exhibits a qualitatively similar pattern regardless of the nature of the shocks. Fujita (2011) and Campolieti *et al.* (2012) use sign restrictions consistent with the Beveridge curve relationship to differentiate the aggregate negative/positive shocks depending on how unemployment and vacancies respond to such shocks. These existing studies all look into aggregate data at national level. To implement sign restrictions becomes more difficult, if not impossible, for our large VAR that involves 33 endogenous regional labour market variables. To start with, as shown in Wall and Zoega (2002), the Beveridge curve relationship does not necessarily hold for every UK region. Next, it becomes even harder to impose meaningful structures on how changes in one variable might affect variables in other regions. To circumvent these problems, we resort to GSMs to explore the spillover effects in a data based manner.

The spatial dynamics of labour market variables in the UK regions was a topic of significant interest to economists in the wake of the recessions of the 1980s and 1990s. Manning (1994) found strong contiguity effects in his analysis of county labour market data. Martin (1997) found co-integrating relationships between regional and national unemployment rates, suggesting the existence of equilibrium differentials between regions and a tendency for shocks to be transmitted speedily across geographies. Evans and McCormick (1994), Taylor and Bradley (1994), and McCormick (1997) investigate the role of, *inter alia*, housing markets and long term migration trends in determining regional response to macroeconomic shocks. As the core region grows, migration from the periphery tends to increase, thereby easing labour market shortages in the core while reducing unemployment in the periphery. These papers uncover a marked change, observed in the 1990s recession, in the pattern of regional labour market response to macroeconomic fluctuations, with regions that had previously been characterised by relatively lower levels of unemployment being relatively hard hit. More recent work for the whole of the UK has been scanty[3], but, building on the US work of Crone (2006), Sensier and Artis (2011) investigate the spread of recession over time across the counties of Wales. The work reported in the present paper represents an extension of this to the whole of the UK, while simultaneously employing more recently developed methods of anlaysis to throw greater light on the nature of the transmission mechanism.

Our empirical results shed new light on the interrelationship between job finding, job separation and vacancy rates of 11 UK regions. Our model comparison results indicate that regime changes in the dynamic system are governed by confidence levels. The plot of the transition function shows two marked dips: the first happened right after the Great Recession begins in Q2 2008, while the second happened in the second half of 2010. Moreover, we find that regardless of the regimes, for each variable, both the volatility spillovers to and from other variables are high, which provides clear evidence for the close interdependence between UK regional labour markets. Analysis

[3]There has, however, developed a literature on regional convergence in Europe - see, for example, Duranton and Monastiriotis (2002), Corrado *et al.*(2005) - but the focus of this work is on long run equilibrium differentials rather than on short term responses to cyclical fluctuations.

of net spillovers shows that, in general, shocks to job separation rates tend to spread into job finding and vacancy rates. By contrast, vacancy rates are usually at the receiving ends of shocks transmitted from the unemployment flows. The impact of shocks to outflow rates are mixed. However, there is strong evidence that shocks to outflow rates have larger impact on vacancy rates compared to shocks to inflow rates or vacancy rates.

The remainder of the paper is organised as follows. Section 2 introduces the econometric methods. Section 3 presents the empirical analysis. Section 4 concludes. Bayesian methods and explanations on GSM are provided in an online appendix.

2 Econometric Methods

2.1 Model and Bayesian Methods

The United Kingdom has a relatively flexible labour market (Owen and Green, 1989). The population is concentrated, with large cities linked by a good transport infrastructure. Hence a worker can easily commute to take up a job in a region other than the one in which she resides - though of course this comes at a cost. Moreover, with a high share of private ownership in the housing market, both in the form of owner-occupation and private rentals, migration is straightforward. Consequently, changes in the economic fortunes of one region of the country are typically transmitted to other regions through a process of local labour market adjustments.

When we model the Diamond-Mortensen-Pissarides search/matching mechanism at regional level, it is necessary therefore to allow for interregional interactions. Moreover, there is considerable evidence of nonlinearity in the dynamics of job search/matching process (eg. Shimer, 2007; Elsby *et al.*, 2009; Campolieti *et al.*, 2012). Our modelling strategy therefore needs to allow both for regional spillover and possible nonlinear effects.

Let y_t be a vector containing inflow, outflow and vacancy rates for 11 UK regions. We model the dynamic linkages between these variables using an unrestricted smooth transition VAR:

$$y_t = \Phi + \Sigma_{h=1}^{p} \Gamma_h y_{t-h} + F(z_t) \left[\Phi^z + \Sigma_{h=1}^{p} \Gamma_h^z y_{t-h} \right] + \varepsilon_t, \qquad (1)$$

where ε_t is a white noise process, that is $E(\varepsilon_t) = 0$, $E(\varepsilon_s \varepsilon_t') = \Sigma$ for $s = t$, and $E(\varepsilon_s \varepsilon_t') = 0$ for $s \neq t$.

The regime changes are assumed to be captured by the following first order logistic smooth transition function as explained in Maddala (1977) and Teräsvirta (1994):[4]

$$F(z_t) = \left[1 + exp\left\{-\gamma\left(z_{t-\pi} - c\right)/\sigma\right\}\right]^{-1} \qquad (2)$$

Function (2) is defined by the transition variable $z_{t-\pi}$, where π is the lag indicator. The parameter γ (which is non-negative) determines the speed of the smooth transition. We can see that when $\gamma \to \infty$, the transition function becomes a Dirac function and the model (1) becomes a two-regime threshold VAR model along the lines of Tong (1983). When $\gamma = 0$, the logistic function becomes a constant (equal to 0.5), and the nonlinear model

[4] For a comprehensive review on smooth transition VAR models, please refer to Hubrich and Teräsvirta (2013).

(1) collapses, in this special case, to a linear VAR(p). The parameter c is the point of inflection of the function and so is the threshold around which the dynamics of the model change. The value for the parameter σ is chosen by the researcher; it could, as a particularly simple example, be set to one. However, if we set σ equal to the standard deviation of the process z_t, this effectively normalises γ such that we can give this parameter an interpretation in terms of the precision of z_t (i.e., σ^{-1}) which, in turn, aids in defining the prior for γ. The transition from one extreme regime to the other is smooth for reasonable values of γ.

The principle underlying the logistic smooth transition VAR (LSTVAR) is that as z_t increases, moving from well below some threshold c to well above this threshold, the dynamics of the vector process y_t changes from one regime to another. That is, if z_t is very low - that is, well into what we will call the *lower* regime - then the process y_t may be generated by the VAR model as follows.

$$y_t = \Phi + \Sigma_{h=1}^{p} \Gamma_h y_{t-h} + \varepsilon_t \tag{3}$$

However, when z_t is very high - well into what we will call the *upper* regime - then the process y_t may be generated by the VAR given by

$$y_t = (\Phi + \Phi^z) + \Sigma_{h=1}^{p} \left(\Gamma_h + \Gamma_h^z\right) y_{t-h} + \varepsilon_t = \Phi^1 + \Sigma_{h=1}^{p} \Gamma_h^1 y_{t-h} + \varepsilon_t \tag{4}$$

The transition between these two regimes is smooth - governed by the values of the parameters in the smooth function of z_t denoted by $F(z_t)$. The value of $F(z_t)$ is bounded by 0 and 1 since $F(z_t) = 0$ when $z_t = -\infty$, and $F(z_t) = 1$ when $z_t = \infty$. The presence in the model of the smooth transition between regimes allows nonlinearity to be accommodated, while the inclusion of region-specific data in our vector of endogenous variables allows for the presence of spillover effects.

Following Gefang and Strachan (2011), we rewrite the model in (1) as

$$y_t = (1 - F(z_t)) \left[\Phi + \Sigma_{h=1}^{p} \Gamma_h y_{t-h}\right] + F(z_t) \left[\Phi^1 + \Sigma_{h=1}^{p} \Gamma_h^1 y_{t-h}\right] + \varepsilon_t \quad (5)$$

which is equivalent to equation (1), but this representation shows explicitly the parameters in the different regimes. Note that since z_t is a continuous variable and $F(z_t)$ is a continuous function of z_t, model (1) implies an infinite set of dynamic processes.

Let $x_t = (1, y'_{t-1}, ..., y'_{t-p})$, $x_t^\theta = [x_t \;\; F(z_t)x_t]$, $Y = (y_1, y_2, ..., y_T)'$, $X^\theta = (x_1^{\theta\prime}, x_2^{\theta\prime}, ..., x_T^{\theta\prime})'$, $B = (\Phi, \Gamma_1, ..., \Gamma_p, \Phi^z, \Gamma_1^z, ..., \Gamma_p^z)'$ and $E = (\varepsilon_1, \varepsilon_2, ..., \varepsilon_T)'$. We rewrite model (1) in a more compact form as

$$Y = X^\theta B + E \quad (6)$$

where E is a $T \times N$ matrix for *i.i.d.* error terms with its t^{th} row distributed as $\mathrm{N}(0, \Sigma)$.

Vectorizing the matrices, we can transform model (6) into

$$y = (I_n \otimes X)\beta + e \quad (7)$$

where $y = vec(Y)$, $\beta = vec(B)$, $e = vec(E)$ and $e \sim N(0, \Sigma \otimes I_T)$. Note that the dimension of β is $N^2k \times 1$.

Equation (7) cannot be estimated using frequentist methods when the number of VAR coefficients exceeds the number of observations. The Bayesian VAR approach, which shrinks parameters by employing appropriate priors, has proved powerful for analyzing such dynamic models of large dimensions (e.g., Sims, 1972, 1980; Banbura *et al.*, 2010; Koop, 2011). Recently, Gefang (2014) has introduced the Bayesian DAELasso method for VAR shrinkage. Compared with other Bayesian VAR approaches, DAELasso is more attractive for our current purposes as it does not discriminate between the endogenous variables.

The DAELasso estimator for a VAR is defined as following:

$$\hat{\beta}_{dL} = arg\, min_{\beta} \{ [y - (I_n \otimes X)\beta]' [y - (I_n \otimes X)\beta] + \sum_{j=1}^{N^2k} \lambda_{1,j} |\beta_j| + \sum_{j=1}^{N^2k} \lambda_{2,j} \beta_j^2 \} \tag{8}$$

where $\lambda_{1,j}$ and $\lambda_{2,j}$, for $j = 1, 2, ..., N^2k$, are positive tuning parameters associated with the L_1 and L_2 penalties, respectively. We allow for different tuning parameters for different β_j to allow for different degrees of shrinkage.

The parameters in equation (8), including γ and c in the smooth transition function (2), can be estimated using full conditional Gibbs samplers (Geman and Geman, 1984). To save space, we present the priors, posteriors, full Gibbs scheme and prior sensitivity analysis in the online appendix.

2.2 Generalised Spillover Measure

We use the GSM developed by Diebold and Yilmaz (2012) to decompose forecast error variances of each variable into components that are associated with various shocks to the dynamic system modelled in equation (1). The GSM does not require orthogonal innovations, hence the variance decompositions are invariant to the ordering of the variables. This feature is particular relevant to our current research as there is a lack of economic theories regarding how shocks propagate in the complicated system involving inflow, outflow and vacancy rates of many different regions.

The original GSMs are developed for linear VARs. As the smooth transition function (2) is continuous, we can calculate GSMs for any value of $F(z_t)$ that may be of interest. For example, if we are concerned about the situation where $z_t = z_\tau$, model (1) turns into

$$y_t = (\Phi + \Phi^z F(z_\tau)) + \Sigma_{h=1}^{p} \left(\Gamma_h + \Gamma_h^z F(z_\tau)\right) y_{t-h} + \varepsilon_t \tag{9}$$

Let $\Psi_h = \Gamma_h + \Gamma_h^z F(z_\tau)$, we have the familiar linear VAR form discussed in section 2 of Diebold and Yilmaz (2012). Using the standard technique detailed in section 2.1 of Lütkepohl (2007), we can write equation (9) in its moving average representation:

$$y_t = \mu + \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \tag{10}$$

where μ is the mean, and the moving average coefficients A_i can be computed recursively using $A_0 = I_N$, and $A_i = \sum_{j=1}^{i} A_{i-j}\Psi_j$.

Following Diebold and Yilmaz (2012), based on A_i and Σ, we can then compute the own variance shares for variables y_n that are due to shocks to the variable itself, directional volatility spillovers received by the variable y_n from shocks to other variables and directional volatility spillovers transmitted by the variable y_n to other variables. More importantly, we can evaluate net spillovers and net pairwise spillovers to examine how shocks are transmitted across variables and regions. Again, for brevity, we relegate the details of how we compute these spillovers to the online appendix.

3 Empirical Analysis

3.1 Data Description

The main data series used in the present analysis provide labour market information within standard UK regions and come from Nomis.[5] Monthly data are published on flows of workers into and out of the unemployment register, notified vacancies,[6] unemployment (known as the claimant count) and unemployment rates (workplace-based estimates). For reasons of data availability, our sample period runs from May 2002 to November 2012. We seasonally adjust the variables in our analysis using the X-12-ARIMA seasonal adjustment program of the US Census Bureau. There is an obvious step change in the seasonally adjusted vacancy data in June 2003 when the Employer Direct Online facility was introduced - this allows employers to register vacancies at job centres much more easily than was previously possible. We use a dummy variable to control for this change in data handling procedures. In line with the literature (Pissarides and Wadsworth, 1989;

[5] Nomis, previously known as the National Online Manpower Information System, produces detailed spatial labour market data and makes these available at www.nomisweb.co.uk.

[6] Nomis also publish the stock of unfilled vacancies, which tend to have unspecified time lags because follow up takes time. By contrast, notified vacancies do not have the time lag problem. Qualitatively, notified vacancies are similar to the US help wanted index, vacancy posting used in papers such as Fujita (2011) and Campolieti *et al.* (2012).

Albæk and Hansen, 2004; Burgess and Turon, 2005), we calculate the inflow rate (s) as the ratio of the flows of workers onto the unemployment register to the number of employed workers, the outflow rate (f) as the ratio of the flows out of the unemployment register to the number of people who are unemployed,[7] and the vacancy rate (v) as the ratio of notified vacancies to the number of labour force (sum of the employed and unemployed). Finally, to remove the excess volatility featured in high-frequency monthly data, we use quarterly averages of the monthly data in our analysis. Altogether, we consider 11 regions, i.e., North East (NE), North West (NW), Yorkshire and The Humber (Y & H), East Midlands (EM), West Midlands (WM), East, London, South East (SE), South West (SW), Wales and Scotland.

Studies such as Friedman (1997), Acemoglu and Scott (1994), and Stock and Watson (1999) suggest that the regional labour market may be affected by macroeconomic variables that are linked to expectations, output, inflation and monetary policies at national level. Moreover, it is possible that regime changes in the interrelationships between regional variables might be governed by their national aggregates. Thus, we consider the following 7 UK macro series as candidate transition variables for equation (2): confidence indicators produced in consumer opinion surveys, total industrial production, registered unemployment rate, money supply (M2), total unfilled job vacancies, the consumer price index and interest rate (discount rate). The first six series are obtained from OECD Main Economic Indicators, while interest rate is from International Financial Statistics. The raw data are

[7] As argued by Shimer (2007), in a steady state, the relationship between worker flows and the unemployment rate can be expressed as $s/(s+f)$ where s is the inflow rate and f the outflow rate. The data we use match this function well.

in monthly frequencies. Again, we use X-12-ARIMA of the US Census Bureau to seasonally adjust the variables where needed, and take the quarterly average to eliminate any excess volatilities.

The standardised inflow, outflow and vacancy rates for 11 UK regions are plotted in Figures 1-3. There is pronounced evidence of a common trend in each figure.[8] Empirical literature on macro time series at disaggregated levels identify the common trend as a factor which is driven by the broad business cycle trends for the economy as a whole (Altonji and Ham, 1990; Kose *et al.*, 2003; Campolieti *et al.*, 2013). Since we are more interested in the effect of regional specific shocks, we remove the effect of the common factor from the data before estimating the model (1).[9]

[8] To avoid the graphs becoming too messy, we omit labels for the multiple series. There are, however, some notable cases of regions where, with the onset of the Great Recession in 2008, the flows into and out of employment differed from the bulk of other regions. In Figure 1, we see that there are two regions that experienced a particularly dramatic fall in the inflow rate, and that this rate recovered more quickly than elsewhere - the two regions are Scotland and Wales. Likewise, in Figure 2 the outflow rates of these two regions at this time take deeper drops.

[9] Jimeno and Bentolila (1998) also argue that when analyze regional labour market variables, it is important to differentiate aggregate and regional specific shocks in an integrated economy. They use regional labour market variables expressed as deviations from the corresponding national means to tackle the problem. Compared to theirs, our method can better disentangle the common effect and regional specific effects.

Figure 1: Standardised Inflow Rates

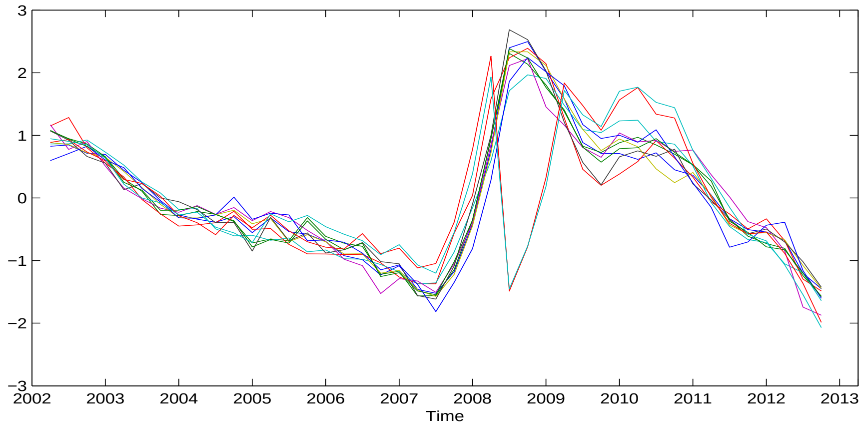


Figure 2: Standardised Outflow Rates

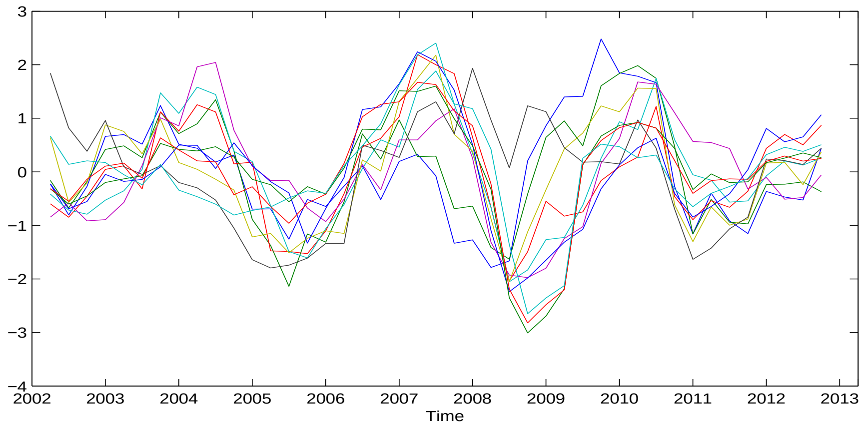
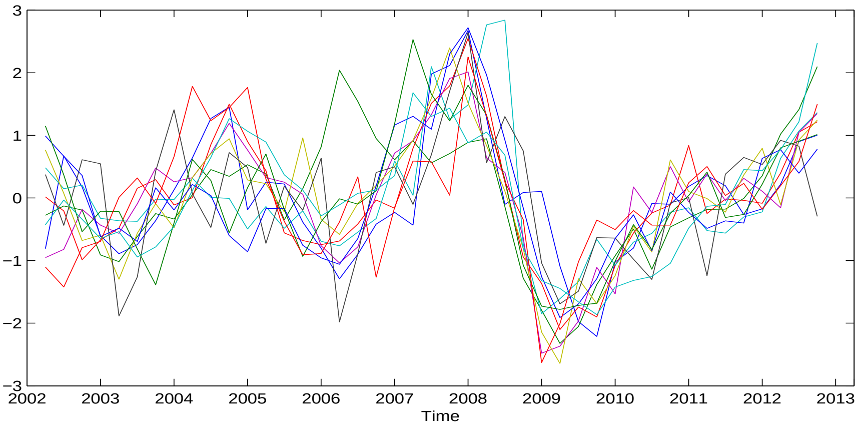


Figure 3: Standardised Vacancy Rates



3.2 Model Comparisons

The Akaike information criterion (AIC) and Bayesian information criterion (BIC) suggest a lag length of 1 or 2 quarters for linear trivariate VAR models that contain the inflow, outflow and vacancy rates for each region. For the large non-linear VAR model that contains all the 33 UK regional inflow, outflow and vacancy rates, we consider a large number of alternative VAR models. The VARs have lag lengths of 1 or 2 quarters; each of the transition variables is considered in logged level terms and in terms of first differences (growth rates) and each of these (level or growth) transition variables appears in the model separately with the lag length of 1, 2, 3 or 4 to allow for a long enough time period during which the regime of labour market interactions begins to react to macroeconomic changes. Hence we estimate (2 x 7 x 2 x 4 =) 112 candidate models differentiated by the lag order of VAR, the transition variable (and whether that appears in level or change terms), and the lag order of the transition variable. In empirical work, each

Gibbs sampler runs 1,1000 iterations with the first 1000 discarded.

We use the BIC defined below for model comparisons.

$$BIC = -log(\hat{l}) + 0.5log(T)d \tag{11}$$

where $\hat{l}$ is the maximum of the likelihood function and d is the number of parameters including the VAR coefficients and the parameters in the logistic function. The method is appealing as it does not involve integration and does not depend on the priors (Wasserman, 2000).

The top 10 preferred models as selected by BIC are listed in Table 1. The general finding is that the lagged consumer confidence indicator in levels is the most effective series in the identification of regime changes, followed by the growth rate of industrial production. Models with transition variables associated with inflation and monetary policy also ranked highly. However, models with transition variables related to national unemployment and vacancies do not appear in the top 10 selected models. Our result that consumer confidence level outperforms the rest of the candidate variables in leading regime changes in intra- and inter- regional labour market interdependencies is in the spirit of Acemoglu and Scott's (1994) finding that consumer confidence can forecast UK unemployment changes better than other macroeconomic variables.[10]

As shown in Kass and Raftery (1995), the Bayes factor can be approxi-

[10] Although further investigation on why consumer confidence plays such an important role goes beyond the scope of the current paper, we would like to point out that recent papers that focus on individuals' dual role as consumers and workers might provide more insights on this issue. For instance, Crouch (2012) explores the possibility of resolving the tension between an economy's need for both flexible workers and confident consumers.

mated by the exponential of $-\frac{1}{2}$ times the differences between two models' BIC measures calculated by equation (11). If we assume uniform prior model probabilities, the preferred model will receive almost 100% of the posterior probability. Since there is no strong theoretical justification for assigning models different prior probabilities, we take the model selected by BIC as our preferred model and use it for the rest of the analysis.

Table 1: Model Comparison Results

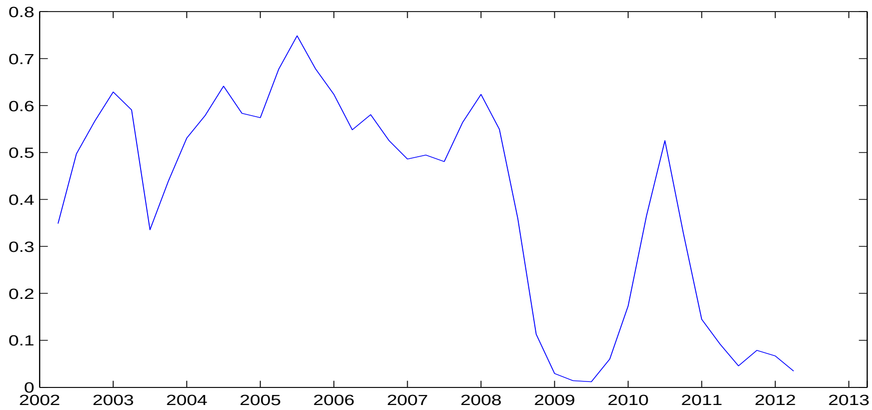
Model	Transition Variable	Lag Length of Transition Variable	Order of VAR	BIC
1	Consumer Confidence Indicators (level)	4	2	34.85
2	Industry Production (first difference)	2	2	-26.80
3	CPI (first difference)	4	2	-42.50
4	M2 (first difference)	2	2	-46.89
5	CPI (first difference)	1	2	-62.11
6	Interest Rate (first difference)	1	2	-72.70
7	Consumer Confidence Indicators (level)	2	2	-73.19
8	M2 (first difference)	1	2	-79.37
9	Interest Rate (first difference)	4	2	-80.13
10	Consumer Confidence Indicators (first difference)	4	2	-100.87

Notes:
The top 10 are selected out of 112 candidate models.

3.3 Nonlinear Effect in the Most Preferred Model

We plot the value of the smooth transition function against time for the most preferred model in Figure 4. Note that here the transition indicator is consumer confidence in levels, and the lag length of the indicator is one year. The most striking feature of the plot is the huge impact of the Great Recession which starts in 2008. Before then, the values taken by the transition indicator are relatively high and the changes are rather smooth. After the recession hit, the regime changed abruptly. The value of the transition function jumped towards a very low level close to zero. This situation only starts to get better after early 2010. However, the recovery is very short lived, and the value of the logistic function takes another dive at the end of 2010. Interestingly, we find that the first drop to the lower regime happens after the Great Recession sets in in 2008, yet the second fall in the regimes happens well before growth once again slows in 2012. Overall, our result supports the notion that the Great Recession greatly changed the regional and interregional job search/matching process in the UK. We investigate further how this switch manifests itself in the next section of the paper.

Figure 4: Transition Function



3.4 Spillovers

We study how shocks are transferred between variables by investigating spillovers under three hypothetical regimes: a lower regime where the value of the transition function is 0, an upper regime where the value of the transition function is 1, and a middle regime where the transition function is 0.5. In practice, as we have seen the upper regime approximates the position before the Great Recession while the lower regime approximates the position since. For each regime, we consider two forecasting horizons: $h = 2$ and $h = 4$.

Table 2: Directional Spillover From Others

Variable	Region	Lower Regime h=2	Lower Regime h=4	Middle Regime h=2	Middle Regime h=4	Upper Regime h=2	Upper Regime h=4
	NE	0.9662	0.9679	0.9621	0.9658	0.9642	0.9678
	NW	0.9701	0.9684	0.9696	0.9696	0.9669	0.9682
	Y & H	0.9714	0.9688	0.9653	0.9676	0.9606	0.9654
	EM	0.9762	0.9726	0.9757	0.9716	0.9745	0.9698
	WM	0.9761	0.9761	0.9766	0.9749	0.9744	0.9703
s	East	0.9561	0.9618	0.9577	0.9644	0.9615	0.9653
	London	0.9747	0.9760	0.9748	0.9741	0.9739	0.9723
	SE	0.9666	0.9661	0.9712	0.9697	0.9723	0.9680
	SW	0.9743	0.9706	0.9730	0.9680	0.9700	0.9673
	Wales	0.9715	0.9682	0.9679	0.9645	0.9664	0.9625
	Scotland	0.9722	0.9683	0.9715	0.9669	0.9706	0.9672
	NE	0.9562	0.9559	0.9599	0.9580	0.9646	0.9647
	NW	0.9567	0.9622	0.9625	0.9629	0.9686	0.9644
	Y & H	0.9693	0.9675	0.9628	0.9668	0.9618	0.9653
	EM	0.9739	0.9688	0.9705	0.9681	0.9686	0.9692
	WM	0.9768	0.9743	0.9784	0.9737	0.9768	0.9722
f	East	0.9739	0.9717	0.9743	0.9723	0.9739	0.9735
	London	0.9648	0.9619	0.9596	0.9596	0.9587	0.9625
	SE	0.9778	0.9731	0.9749	0.9716	0.9691	0.9663
	SW	0.9734	0.9705	0.9772	0.9721	0.9753	0.9709
	Wales	0.9759	0.9717	0.9779	0.9716	0.9746	0.9713
	Scotland	0.9643	0.9654	0.9579	0.9639	0.9576	0.9634
	NE	0.9767	0.9720	0.9682	0.9670	0.9647	0.9687
	NW	0.9490	0.9600	0.9550	0.9666	0.9659	0.9721
	Y & H	0.9772	0.9726	0.9770	0.9701	0.9736	0.9679
	EM	0.9694	0.9673	0.9648	0.9677	0.9624	0.9668
	WM	0.9706	0.9728	0.9718	0.9720	0.9686	0.9673
v	East	0.9610	0.9661	0.9627	0.9674	0.9637	0.9657
	London	0.9562	0.9666	0.9604	0.9684	0.9669	0.9710
	SE	0.9720	0.9721	0.9775	0.9751	0.9781	0.9727
	SW	0.9510	0.9587	0.9538	0.9639	0.9623	0.9711
	Wales	0.9777	0.9727	0.9820	0.9735	0.9795	0.9701
	Scotland	0.9735	0.9722	0.9737	0.9729	0.9740	0.9716

Notes:

We use s to denote inflow rate, f to denote outflow rate and v to denote vacancy rate.

Table 2 presents the directional spillover *from* other variables. For each variable, the spillovers from others are high. Generally, the values range between 95% to 98% for each regime. There are some slight differences between the regimes though. For example, variables typically receive fewer spillovers from other variables when the regime moves from the upper to the lower regime. These findings may explain the relatively slow transmission of economic recovery from the leading regions to other parts of the country over the course of the 2013-14 upturn (compared, that is, with earlier recoveries).

Table 3 shows the directional volatility spillover *to* other variables. There is much more variation across regions in the extent of spillover in this table than in Table 2; while labour market conditions spread across space, the economic structure of some regions (specialising perhaps in industries with strong input-output linkages) means that they are more likely than others to serve as leaders in the diffusion of labour market shocks. On average, volatilities of inflow and outflow rates tend to have the highest directional spillovers to others at the lower regime, followed by the middle regime, then have much smaller directional spillovers to others at the upper regime. The scenario related to vacancy is mixed. Directional spillovers to others tend to have the largest values at the upper regime, followed by the middle regime, then the upper regime.

The large values of directional spillovers reported in Tables 2-3 confirm, unsurprisingly, that the 33 endogenous variables we investigated are closely interrelated and that it would therefore be inappropriate to ignore interregional linkages when we model the regional labour market.

Table 3: Directional Spillover To Others

Variable	Region	Lower Regime h=2	Lower Regime h=4	Middle Regime h=2	Middle Regime h=4	Upper Regime h=2	Upper Regime h=4
	NE	1.0400	1.0373	1.0044	1.0149	0.9636	0.9768
	NW	1.0132	1.0190	0.9939	0.9789	1.0136	0.9731
	Y & H	0.9808	1.0043	1.0454	1.0543	1.0706	1.0732
	EM	1.0385	1.0388	0.9443	0.9527	0.8768	0.8991
	WM	0.7799	0.7942	0.8286	0.8758	0.9164	0.9683
s	East	1.0702	1.0515	1.0448	1.0149	1.0292	1.0069
	London	0.9107	0.8805	0.8982	0.8710	0.8941	0.8762
	SE	1.0003	0.9885	0.9774	1.0057	0.9697	1.0009
	SW	0.9616	0.9571	0.9584	0.9716	0.9937	1.0220
	Wales	1.1233	1.1165	1.1482	1.1654	1.1180	1.1423
	Scotland	1.1550	1.1267	1.1568	1.1466	1.0983	1.0868
	NE	1.0634	1.0969	1.0300	1.0840	0.9382	0.9854
	NW	1.0445	1.0689	1.0930	1.1113	1.0420	1.0236
	Y & H	1.0133	1.0508	1.0547	1.0873	1.0996	1.0998
	EM	0.9730	0.9864	0.9508	0.9709	0.9394	0.9516
	WM	0.8968	0.8993	0.8986	0.8992	0.8767	0.8801
f	East	0.9348	0.9468	0.9255	0.9467	0.8955	0.9098
	London	1.0702	1.1033	1.0650	1.1057	1.0190	1.0550
	SE	0.9375	0.9509	1.0392	1.0433	1.1456	1.1414
	SW	1.0016	1.0215	0.9380	0.9607	0.9023	0.9216
	Wales	0.9572	0.9842	0.9169	0.9728	0.9295	0.9661
	Scotland	1.0066	1.0112	1.0398	1.0461	0.9911	1.0023
	NE	0.8406	0.7891	0.8822	0.8220	0.9168	0.8926
	NW	0.9566	0.9695	0.8581	0.8330	0.8236	0.8054
	Y & H	0.8909	0.8720	0.9011	0.8795	0.9584	0.9348
	EM	0.9546	0.9599	1.0011	0.9628	1.0307	1.0026
	WM	0.8390	0.8355	0.8838	0.8941	0.9373	0.9657
v	East	0.9709	0.9517	1.0109	0.9687	1.0864	1.0405
	London	0.8090	0.7988	0.7382	0.7187	0.7478	0.7222
	SE	0.8698	0.8547	0.8500	0.8606	0.8489	0.8648
	SW	0.8282	0.8397	0.7961	0.8133	0.8172	0.8127
	Wales	1.0231	0.9768	1.0951	0.9653	1.1071	0.9866
	Scotland	1.0181	0.9788	0.9998	0.9645	0.9671	0.9626

Notes:

We use s to denote inflow rate, f to denote outflow rate and v to denote vacancy rate.

Table 4: Net Spillover To All Other Variables

Variable	Region	Lower Regime h=2	Lower Regime h=4	Middle Regime h=2	Middle Regime h=4	Upper Regime h=2	Upper Regime h=4
	NE	0.0738	0.0694	0.0424	0.0491	-0.0007	0.0090
	NW	0.0431	0.0506	0.0244	0.0093	0.0468	0.0049
	Y & H	0.0095	0.0355	0.0801	0.0867	0.1100	0.1078
	EM	0.0623	0.0662	-0.0314	-0.0189	-0.0977	-0.0707
	WM	-0.1963	-0.1819	-0.1480	-0.0991	-0.0580	-0.0021
s	East	0.1141	0.0897	0.0871	0.0505	0.0678	0.0416
	London	-0.0639	-0.0956	-0.0766	-0.1032	-0.0798	-0.0961
	SE	0.0337	0.0224	0.0062	0.0360	-0.0025	0.0329
	SW	-0.0127	-0.0135	-0.0146	0.0036	0.0237	0.0547
	Wales	0.1518	0.1484	0.1803	0.2009	0.1516	0.1797
	Scotland	0.1828	0.1583	0.1853	0.1797	0.1277	0.1196
	NE	0.1072	0.1409	0.0701	0.1261	-0.0264	0.0207
	NW	0.0877	0.1068	0.1305	0.1485	0.0735	0.0592
	Y & H	0.0439	0.0833	0.0919	0.1205	0.1378	0.1345
	EM	-0.0009	0.0176	-0.0197	0.0028	-0.0292	-0.0176
	WM	-0.0800	-0.0750	-0.0799	-0.0744	-0.1001	-0.0921
f	East	-0.0391	-0.0248	-0.0488	-0.0256	-0.0784	-0.0637
	London	0.1053	0.1414	0.1054	0.1461	0.0603	0.0925
	SE	-0.0403	-0.0223	0.0643	0.0717	0.1765	0.1750
	SW	0.0281	0.0510	-0.0392	-0.0114	-0.0729	-0.0493
	Wales	-0.0188	0.0124	-0.0611	0.0011	-0.0451	-0.0052
	Scotland	0.0423	0.0458	0.0819	0.0823	0.0335	0.0389
	NE	-0.1361	-0.1829	-0.0860	-0.1450	-0.0479	-0.0760
	NW	0.0076	0.0095	-0.0969	-0.1336	-0.1423	-0.1667
	Y & H	-0.0864	-0.1006	-0.0759	-0.0906	-0.0152	-0.0331
	EM	-0.0148	-0.0074	0.0362	-0.0049	0.0684	0.0358
	WM	-0.1316	-0.1373	-0.0880	-0.0779	-0.0312	-0.0015
v	East	0.0098	-0.0143	0.0482	0.0013	0.1227	0.0748
	London	-0.1472	-0.1679	-0.2223	-0.2497	-0.2191	-0.2488
	SE	-0.1022	-0.1174	-0.1275	-0.1145	-0.1291	-0.1079
	SW	-0.1227	-0.1190	-0.1578	-0.1506	-0.1451	-0.1584
	Wales	0.0454	0.0041	0.1131	-0.0082	0.1275	0.0165
	Scotland	0.0446	0.0066	0.0261	-0.0084	-0.0069	-0.0090

Notes:

We use s to denote inflow rate, f to denote outflow rate and v to denote vacancy rate.

Net spillovers from each variable to all the other variables are reported in Table 4. Observe that shocks to inflow rates tend to have more impact on the volatilities of other variables - with a preponderance of positive figures in this part of the table. The net spillovers associated with Wales and Scotland are particularly high, reflecting the fact that changes in the inflow rate in these regions have marked effects on other aspects of the labour market both within these regions and elsewhere. By way of contrast, the figures in the part of the table that refers to vacancy rates are predominantly negative. The figures related to outflows are mixed. Among them, London exhibits the largest positive net spillovers under the both the lower and upper regimes, this serving to highlight the key leading role played by the capital.

Tables 5-7 report respectively the net impact of shocks to one region's inflows on inflows of all other regions, the net impact of shocks to one region's inflows on all outflows, and the net impact of shocks to one region's inflows on vacancies of all regions. Table 5 shows that the volatility in inflows associated with the South East, South West and Scotland tend to have positive spillovers to inflows of other regions under all regimes. Yorkshire and Humberside and the West Midlands tend to have negative spillovers. The scenarios for other regions are quite mixed. Table 6 shows that shocks to inflows in North East, East, Wales and Scotland tend to make outflows more volatile as a whole, while shocks to inflows in East Midlands, West Midlands, London and South East tend to dampen the volatilities in outflows of all regions. Table 7 provides evidence that in most cases, shocks to inflows tend to increase the volatilities on vacancies.

Tables 8-10 present respectively the net impacts of shocks to one region's

Table 5: Net Spillovers From Each Regional Inflows To Inflows Of All Other Regions

Region	Lower Regime h=2	Lower Regime h=4	Middle Regime h=2	Middle Regime h=4	Upper Regime h=2	Upper Regime h=4
NE	0.0118	0.0019	0.0131	-0.0017	-0.0087	-0.0126
NW	-0.0067	0.0027	0.0031	-0.0075	0.0132	-0.0045
Y & H	-0.0337	-0.0098	-0.0296	-0.0036	-0.0096	0.0087
EM	0.0400	0.0393	-0.0178	-0.0070	-0.0565	-0.0318
WM	-0.1027	-0.0777	-0.0738	-0.0576	-0.0434	-0.0190
East	-0.0130	-0.0063	-0.0025	-0.0081	0.0079	-0.0029
London	0.0261	-0.0187	0.0396	-0.0307	0.0266	-0.0403
SE	0.0435	0.0091	0.0395	0.0260	0.0200	0.0104
SW	0.0183	0.0015	0.0009	0.0020	0.0009	0.0054
Wales	-0.0201	0.0141	0.0022	0.0413	0.0269	0.0510
Scotland	0.0365	0.0439	0.0253	0.0470	0.0227	0.0355

Table 6: Net Spillovers From Each Regional Inflows To Outflows Of All Regions

Region	Lower Regime h=2	Lower Regime h=4	Middle Regime h=2	Middle Regime h=4	Upper Regime h=2	Upper Regime h=4
NE	0.0546	0.0231	0.0293	0.0221	0.0022	0.0095
NW	0.0129	0.0028	-0.0037	-0.0188	0.0104	-0.0121
Y & H	-0.0070	-0.0013	0.0072	0.0197	0.0140	0.0338
EM	-0.0719	-0.0323	-0.0768	-0.0519	-0.0509	-0.0407
WM	-0.0835	-0.0764	-0.0758	-0.0435	-0.0254	-0.0061
East	0.0707	0.0384	0.0564	0.0136	0.0423	0.0131
London	-0.0560	-0.0759	-0.0803	-0.0812	-0.0850	-0.0528
SE	-0.0071	-0.0138	-0.0240	-0.0198	-0.0171	-0.0020
SW	0.0038	-0.0079	0.0082	-0.0112	0.0125	0.0130
Wales	0.0813	0.0438	0.1013	0.0654	0.0758	0.0623
Scotland	0.0792	0.0301	0.0978	0.0453	0.0634	0.0304

Table 7: Net Spillovers From Each Regional Inflows To Vacancies Of All Regions

Region	Lower Regime h=2	Lower Regime h=4	Middle Regime h=2	Middle Regime h=4	Upper Regime h=2	Upper Regime h=4
NE	0.0075	0.0444	-0.0001	0.0287	0.0058	0.0121
NW	0.0369	0.0450	0.0250	0.0356	0.0231	0.0215
Y & H	0.0502	0.0466	0.1025	0.0707	0.1056	0.0653
EM	0.0941	0.0592	0.0632	0.0400	0.0097	0.0017
WM	-0.0101	-0.0278	0.0016	0.0020	0.0108	0.0230
East	0.0564	0.0577	0.0332	0.0449	0.0176	0.0314
London	-0.0341	-0.0010	-0.0359	0.0087	-0.0214	-0.0030
SE	-0.0026	0.0272	-0.0093	0.0298	-0.0054	0.0245
SW	-0.0349	-0.0071	-0.0237	0.0128	0.0103	0.0363
Wales	0.0906	0.0905	0.0768	0.0943	0.0490	0.0665
Scotland	0.0671	0.0844	0.0622	0.0874	0.0416	0.0537

outflows on outflows of all other regions, the net impact of shocks to one region's outflows on all inflows, and the net impact of shocks to one region's outflows on vacancies of all regions. Table 8 shows that under all regimes, Yorkshire and Humberside tends to exert a positive effect on volatilities of outflows in other regions, while the West Midlands, East and South West are receivers of outflow volatility spillovers originated from other regions. Perhaps the most interesting feature of this table, though, is the sign reversals that may be observed for some regions as we move from the lower to the upper regime. For example, with h=2, there are positive spillovers out of London in the lower regime, but negative spillovers in the higher regime. In the wake of recession, outflows from the unemployment register in the capital have a positive impact on outflows elsewhere, serving to pull the country as a whole out of recession; but as the economy grows and we move to the upper regime, this effect is reversed.

Table 9 shows that in most cases the impact of shocks to outflows tend to dampen the volatilities in inflows. By way of contrast, Table 10 provides strong evidence that shocks to outflows generally increase the volatilities in vacancies. Note that under the lower and middle regimes, the net spillovers from outflows in London to UK vacancy rate amount to around 10%. At the upper regime, Yorkshire and Humberside, London and South East regions all have a strong positive effect on volatilities in vacancies.

Tables 11-13 present respectively the net impact of shocks to one region's vacancies on vacancies of all other regions, the net impact of shocks to one region's vacancies on all inflows, and the net impact of shocks to one region's vacancies on outflows of all regions. Table 11 shows that the East Midlands,

Table 8: Net Spillover From Each Regional Outflows To Outflows Of All Other Regions

Region	Lower Regime h=2	Lower Regime h=4	Middle Regime h=2	Middle Regime h=4	Upper Regime h=2	Upper Regime h=4
NE	0.0073	0.0135	-0.0042	0.0079	-0.0231	-0.0058
NW	-0.0252	-0.0053	-0.0116	0.0083	-0.0040	0.0002
Y & H	0.0337	0.0224	0.0393	0.0230	0.0379	0.0261
EM	0.0129	0.0109	0.0161	0.0118	0.0111	-0.0034
WM	-0.0330	-0.0333	-0.0415	-0.0427	-0.0436	-0.0444
East	-0.0178	-0.0212	-0.0244	-0.0318	-0.0267	-0.0380
London	0.0158	0.0303	-0.0006	0.0089	-0.0005	0.0115
SE	0.0165	-0.0119	0.0622	0.0372	0.0786	0.0682
SW	-0.0281	-0.0093	-0.0606	-0.0433	-0.0486	-0.0317
Wales	0.0082	0.0059	-0.0019	0.0118	0.0036	0.0139
Scotland	0.0097	-0.0021	0.0272	0.0087	0.0154	0.0036

Table 9: Net Spillover From Each Regional Outflows To Inflows Of All Regions

Region	Lower Regime h=2	Lower Regime h=4	Middle Regime h=2	Middle Regime h=4	Upper Regime h=2	Upper Regime h=4
NE	0.0807	0.0911	0.0484	0.0668	-0.0051	0.0028
NW	0.0818	0.0701	0.1090	0.0747	0.0730	0.0212
Y & H	-0.0183	0.0203	0.0132	0.0376	0.0473	0.0354
EM	-0.0442	-0.0280	-0.0671	-0.0389	-0.0580	-0.0245
WM	-0.0502	-0.0477	-0.0475	-0.0497	-0.0540	-0.0460
East	-0.0215	-0.0174	-0.0272	-0.0192	-0.0402	-0.0318
London	-0.0195	0.0189	-0.0132	0.0215	-0.0099	0.0099
SE	-0.0391	-0.0221	-0.0059	-0.0096	0.0575	0.0327
SW	-0.0190	-0.0030	-0.0326	-0.0163	-0.0424	-0.0320
Wales	-0.0240	-0.0108	-0.0335	-0.0153	-0.0162	-0.0151
Scotland	-0.0038	-0.0019	0.0168	0.0088	0.0060	-0.0011

Table 10: Net Spillover From Each Regional Outflows To Vacancies Of All Regions

Region	Lower Regime h=2	Lower Regime h=4	Middle Regime h=2	Middle Regime h=4	Upper Regime h=2	Upper Regime h=4
NE	0.0193	0.0364	0.0260	0.0514	0.0017	0.0237
NW	0.0312	0.0419	0.0332	0.0655	0.0045	0.0378
Y & H	0.0285	0.0406	0.0394	0.0599	0.0526	0.0729
EM	0.0303	0.0347	0.0312	0.0299	0.0177	0.0103
WM	0.0032	0.0060	0.0091	0.0179	-0.0025	-0.0017
East	0.0003	0.0138	0.0028	0.0254	-0.0115	0.0061
London	0.1090	0.0922	0.1192	0.1156	0.0707	0.0711
SE	-0.0177	0.0117	0.0080	0.0440	0.0404	0.0742
SW	0.0752	0.0632	0.0540	0.0482	0.0181	0.0145
Wales	-0.0030	0.0173	-0.0257	0.0046	-0.0324	-0.0039
Scotland	0.0364	0.0498	0.0379	0.0647	0.0122	0.0364

East, Wales and Scotland are always net givers in terms of vacancies to vacancies, while Yorkshire and Humberside, London, South East and South West are always receivers. Table 12 implies that, in general, shocks to vacancies tend to decrease the volatilities in inflows. Note that most of the figures in this table have negative values. Especially, shocks to London's vacancy rate tend to decrease the volatilities in inflow rates to around 10% under all regimes. Table 13 shows that shocks to vacancies tend to have negative impact on the variations in outflows.

Table 11: Net Spillover From Each Regional Vacancies To Vacancies Of All Other Regions

Region	Lower Regime h=2	Lower Regime h=4	Middle Regime h=2	Middle Regime h=4	Upper Regime h=2	Upper Regime h=4
NE	-0.0116	-0.0335	0.0253	-0.0197	0.0283	-0.0090
NW	0.0269	0.0208	0.0101	-0.0010	-0.0201	-0.0239
Y & H	-0.0365	-0.0229	-0.0343	-0.0219	-0.0163	-0.0009
EM	0.0207	0.0334	0.0333	0.0335	0.0362	0.0344
WM	-0.0399	-0.0342	-0.0171	-0.0098	0.0097	0.0075
East	0.0303	0.0301	0.0272	0.0333	0.0480	0.0447
London	-0.0484	-0.0310	-0.0718	-0.0432	-0.0777	-0.0573
SE	-0.0332	-0.0255	-0.0324	-0.0072	-0.0226	-0.0042
SW	-0.0170	-0.0117	-0.0340	-0.0214	-0.0391	-0.0263
Wales	0.0440	0.0336	0.0403	0.0289	0.0312	0.0283
Scotland	0.0647	0.0408	0.0533	0.0286	0.0223	0.0066

Table 12: Net Spillover From Each Regional Vacancies To Inflows Of All Regions

Region	Lower Regime h=2	Lower Regime h=4	Middle Regime h=2	Middle Regime h=4	Upper Regime h=2	Upper Regime h=4
NE	-0.0576	-0.0753	-0.0404	-0.0486	-0.0244	-0.0232
NW	0.0118	0.0063	-0.0501	-0.0690	-0.0754	-0.0729
Y & H	-0.0106	-0.0366	-0.0193	-0.0399	-0.0085	-0.0268
EM	-0.0046	-0.0198	0.0144	-0.0022	0.0162	0.0195
WM	-0.0589	-0.0680	-0.0763	-0.0575	-0.0652	-0.0178
East	0.0095	-0.0114	0.0365	0.0017	0.0438	0.0175
London	-0.0816	-0.0865	-0.0984	-0.1047	-0.0862	-0.0937
SE	-0.0498	-0.0473	-0.0758	-0.0494	-0.0853	-0.0408
SW	-0.0509	-0.0492	-0.0480	-0.0684	-0.0434	-0.0760
Wales	-0.0380	-0.0286	0.0283	-0.0205	0.0632	-0.0117
Scotland	0.0095	-0.0028	0.0336	0.0036	0.0186	-0.0067

To summarise, six important features leap out from Tables 6-13. First, outflows from London show that this region is the most important volatil-

Table 13: Net Spillover From Each Regional Vacancies To Outflows Of All Regions

Region	Lower Regime h=2	Lower Regime h=4	Middle Regime h=2	Middle Regime h=4	Upper Regime h=2	Upper Regime h=4
NE	-0.0669	-0.0741	-0.0708	-0.0768	-0.0518	-0.0439
NW	-0.0312	-0.0175	-0.0569	-0.0637	-0.0467	-0.0699
Y & H	-0.0393	-0.0411	-0.0223	-0.0287	0.0096	-0.0054
EM	-0.0309	-0.0211	-0.0115	-0.0362	0.0160	-0.0181
WM	-0.0328	-0.0352	0.0055	-0.0106	0.0243	0.0088
East	-0.0300	-0.0330	-0.0155	-0.0337	0.0309	0.0126
London	-0.0173	-0.0505	-0.0521	-0.1018	-0.0552	-0.0979
SE	-0.0192	-0.0446	-0.0192	-0.0579	-0.0213	-0.0628
SW	-0.0548	-0.0582	-0.0758	-0.0607	-0.0626	-0.0560
Wales	0.0393	-0.0009	0.0445	-0.0165	0.0331	0.0000
Scotland	-0.0296	-0.0314	-0.0609	-0.0405	-0.0478	-0.0089

ity 'giver' affecting vacancies. Its importance in this respect is reduced somewhat in the upper regime (when the economy fares relatively well), suggesting that the capital's role as the engine of the UK economy is particularly important during tough macroeconomic times. Second, outflows tend to have a bigger impact on vacancies than inflows, yet inflows tend to have a bigger impact on outflows than *vice versa*. This provides further evidence that the interlinkages between the three types of variables are rather complicated. Third, our results corroborate Robson's (2001) finding that vacancies play a minor role in accounting for the variations in outflows. Fourth, if we look at $h = 4$, we find that in the lower regime, where the economy is in recession, the net spillovers from inflow to outflow outweigh those from the outflow to inflow, whereas at the middle and upper regime, when the economy is doing better, the net spillovers from outflow to inflow outweigh those from the inflow to outflow. In the literature, there is ongoing debate on whether job separation plays a more important role during recessions (Shimer, 2007; Campolieti, 2011; Elsby *et al.*, 2009). Our empirical analysis is not directly designed to address this issue as we do not focus on the first moments as most of these other papers do. However, our results do demonstrate that if we take the UK regional scenario as a whole, there is evidence that in recessions, the variations in job separation rate increase the variations in job finding rate, while when the economy is in better shape, the volatility spillovers take the opposite direction. Fifth, there is clear evidence that under all three regimes, the spillovers from outflow to vacancy rates are bigger than those from inflow to vacancy rates. Finally, we find that compared with regions in England, Wales and Scotland exhibit higher levels of net spillovers from inflows to other variables under all regimes.

In Tables 14-16 we report, for the lower, middle and higher regimes respectively, the net spillovers between the inflow, outflow and vacancy rate within each region. These being net values, the numbers are again small. There appears to be a pattern in which vacancy rate are 'receivers' in most regions. The evidence on the inflow and outflow rates is more mixed. London and the South East again appear as major net 'givers' in terms of outflows, with Wales consistently being a 'receiver'. The opposite is true of inflows.

4 Conclusion

This paper proposes a smooth-transition VAR model of high dimension to investigate the intra- and inter- regional linkages between the job separation rate, job finding rate and vacancies. Our model is an extension of the standard multivariate matching model explored in Fujita (2011) and Campolieti *et al.* (2012). Using DAELasso of Gefang (2014) and GSM of Diebold and Yilmaz (2012), we are able to track the dynamic volatility spillover mecha-

Table 14: Net Spillovers Within Regions, Lower Regime

	Region	Inflow Rate	Outflow Rate	Vacancy Rate
	NE	0.0050	0.0033	-0.0083
	NW	0.0040	0.0109	-0.0149
	Y & H	-0.0049	0.0155	-0.0106
	EM	-0.0023	0.0122	-0.0098
	WM	-0.0060	-0.0053	0.0113
$h = 2$	East	0.0536	-0.0356	-0.0180
	London	0.0023	-0.0060	0.0037
	SE	0.0216	-0.0005	-0.0211
	SW	0.0041	0.0037	-0.0078
	Wales	0.0277	-0.0486	0.0209
	Scotland	0.0140	-0.0088	-0.0052
	NE	0.0002	0.0127	-0.0129
	NW	-0.0020	0.0089	-0.0069
	Y & H	-0.0039	0.0096	-0.0057
	EM	-0.0009	0.0038	-0.0029
	WM	-0.0027	0.0022	0.0005
$h = 4$	East	0.0274	-0.0180	-0.0094
	London	-0.0053	0.0129	-0.0076
	SE	0.0075	0.0065	-0.0140
	SW	0.0004	0.0050	-0.0054
	Wales	0.0218	-0.0265	0.0047
	Scotland	0.0098	-0.0055	-0.0043

Table 15: Net Spillovers Within Regions, Middle Regime

	Region	Inflow Rate	Outflow Rate	Vacancy Rate
	NE	-0.0043	0.0010	0.0033
	NW	0.0099	0.0213	-0.0312
	Y & H	-0.0102	0.0328	-0.0226
	EM	-0.0032	0.0149	-0.0117
	WM	-0.0086	-0.0067	0.0153
$h = 2$	East	0.0412	-0.0230	-0.0183
	London	0.0015	0.0045	-0.0059
	SE	0.0112	0.0236	-0.0348
	SW	0.0011	0.0036	-0.0047
	Wales	0.0125	-0.0582	0.0457
	Scotland	0.0105	-0.0018	-0.0087
	NE	-0.0063	0.0062	0.0002
	NW	0.0023	0.0201	-0.0224
	Y & H	-0.0033	0.0107	-0.0073
	EM	-0.0013	0.0071	-0.0058
	WM	-0.0029	-0.0050	0.0079
$h = 4$	East	0.0184	-0.0071	-0.0113
	London	-0.0014	0.0190	-0.0176
	SE	0.0025	0.0190	-0.0216
	SW	0.0027	0.0034	-0.0061
	Wales	0.0218	-0.0300	0.0082
	Scotland	0.0027	0.0043	-0.0071

Table 16: Net Spillovers Within Regions, Upper Regime

	Region	Inflow Rate	Outflow Rate	Vacancy Rate
	NE	-0.0057	0.0006	0.0051
	NW	0.0104	0.0138	-0.0242
	Y & H	-0.0129	0.0352	-0.0223
	EM	-0.0053	0.0126	-0.0073
	WM	-0.0036	-0.0082	0.0118
$h = 2$	East	0.0168	-0.0154	-0.0015
	London	-0.0011	0.0115	-0.0104
	SE	-0.0006	0.0336	-0.0330
	SW	0.0056	-0.0015	-0.0041
	Wales	-0.0009	-0.0406	0.0415
	Scotland	0.0060	0.0004	-0.0064
	NE	-0.0053	0.0012	0.0042
	NW	0.0055	0.0145	-0.0200
	Y & H	-0.0018	0.0078	-0.0060
	EM	-0.0047	0.0056	-0.0009
	WM	0.0023	-0.0090	0.0067
$h = 4$	East	0.0055	-0.0068	0.0013
	London	0.0034	0.0177	-0.0211
	SE	0.0012	0.0151	-0.0163
	SW	0.0105	-0.0016	-0.0089
	Wales	0.0156	-0.0197	0.0041
	Scotland	-0.0018	0.0040	-0.0022

nism in 11 UK regions.

Our empirical evidence suggests the existence of close interlinkages between UK regional labour markets, with regime changes driven by confidence. We find that, in general, shocks to job separation rates tend to spread into job finding and vacancy rates. By contrast, vacancy rates are usually at the receiving ends of shocks transmitted from the job separation and finding rates. The impacts of shocks to regional outflow rates are mixed. Yet, there is clear evidence that shocks to outflows play a more important role in affecting the volatilities in vacancy rates than shocks to inflow rates or vacancy rates.

Of particular interest in the context of current policy debates is the changing impact of the job market in London on that of other regions. In the lower regime outflows from unemployment in the capital exert a stronger influence on outflow patterns in other regions than is the case in the higher regime. This offers some reassurance that the current recovery, which has started in London and the surrounding region, will (as has happened in the past) have a beneficial impact on labour markets in other regions. Testing that prediction in real time will, of course, require further research.

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Online Appendix to:
Asymmetric volatility spillovers between UK regional worker flows and vacancies

March 30, 2014

1 Bayesian Methods

The unrestricted nonlinear VAR takes the following form:

$$y_t = \Phi + \Sigma_{h=1}^{p} \Gamma_h y_{t-h} + F(z_t) \left[\Phi^z + \Sigma_{h=1}^{p} \Gamma_h^z y_{t-h} \right] + \varepsilon_t, \qquad (1)$$

where ε_t is a white noise process, that is $E(\varepsilon_t) = 0$, $E(\varepsilon_s \varepsilon_t') = \Sigma$ for $s = t$, and $E(\varepsilon_s \varepsilon_t') = 0$ for $s \neq t$.

The regime changes are assumed to be captured by the following first order logistic smooth transition function:

$$F(z_t) = \left[1 + exp\left\{-\gamma \left(z_{t-\pi} - c\right)/\sigma\right\}\right]^{-1} \qquad (2)$$

First, we rewrite model (1) as

$$y_t = (1 - F(z_t)) \left[\Phi + \Sigma_{h=1}^{p} \Gamma_h y_{t-h} \right] + F(z_t) \left[\Phi^1 + \Sigma_{h=1}^{p} \Gamma_h^1 y_{t-h} \right] + \varepsilon_t \qquad (3)$$

Let $x_t = (1, y_{t-1}', ..., y_{t-p}')$, $x_t^\theta = [x_t \;\; F(z_t)x_t]$, $Y = (y_1, y_2, ..., y_T)'$, $X^\theta = (x_1^{\theta\prime}, x_2^{\theta\prime}, ..., x_T^{\theta\prime})'$, $B = (\Phi, \Gamma_1, ..., \Gamma_p, \Phi^z, \Gamma_1^z, ..., \Gamma_p^z)'$ and $E = (\varepsilon_1, \varepsilon_2, ..., \varepsilon_T)'$. Next, we rewrite model (3) in a more compact form as

$$Y = X^\theta B + E. \qquad (4)$$

where E is a $T \times N$ matrix for *i.i.d.* error terms with its t^{th} row distributed as $\mathrm{N}(0, \Sigma)$.

Vectorizing the matrices, we can transform model (4) into

$$y = (I_n \otimes X)\beta + e \qquad (5)$$

where $y = vec(Y)$, $\beta = vec(B)$, $e = vec(E)$ and $e \sim N(0, \Sigma \otimes I_T)$. Note that the dimension of β is $N^2k \times 1$.

We use the DAELasso estimator defined as following for parameter shrinkages

$$\hat{\beta}_{dL} = arg\ min_{\beta}\{[y-(I_n \otimes X)\beta]^{'}[y-(I_n \otimes X)\beta] + \sum_{j=1}^{N^2k} \lambda_{1,j}|\beta_j| + \sum_{j=1}^{N^2k} \lambda_{2,j}\beta_j^2\} \tag{6}$$

where $\lambda_{1,j}$ and $\lambda_{2,j}$, for $j = 1, 2, ..., N^2k$, are positive tuning parameters associated with the L_1 and L_2 penalties, respectively.

1.1 Priors

Following Gefang (2014), we consider a conditional multivariate mixture prior of the following form:

$$\begin{aligned} \pi(\beta|\Sigma, \Gamma, \Lambda_1, \Lambda_2) \propto \prod_{j=1}^{N^2k} &\{\frac{\sqrt{\lambda_{2,j}}}{\sqrt{2\pi}} exp(-\frac{\lambda_{2,j}}{2}\beta_j^2) \\ &\times \int_0^{\infty} \frac{1}{\sqrt{2\pi f_j(\Gamma))}} exp[-\frac{1}{2f_j(\Gamma)}\beta_j^2] d(f_j(\Gamma))\} \\ &\times \{|M|^{-\frac{1}{2}} exp(-\frac{1}{2}\Gamma^{'} M^{-1}\Gamma)\}^2 \end{aligned} \tag{7}$$

where $\Gamma = [\gamma_1, \gamma_2, ..., \gamma_{N^2k}]^{'}$, $M = \Sigma \otimes I_{Nk}$, and $f_j(\Gamma)$ is a function of Γ and Λ_1 to be defined later.

We need to find an appropriate $f_j(\Gamma)$ which provides us tractable posteriors. The last term in equation (7) takes the form of a multivariate Normal distribution $\Gamma \sim N(0, M)$. For ease of exposition, we first write the $N^2k \times N^2k$ covariance matrix M as following:

$$M = \begin{pmatrix} M_{1,1} & ... & M_{1,j} & M_{1,j+1} & ... & M_{1,N^2k} \\ ... & ... & ... & ... & ... & ... \\ M_{j,1} & ... & M_{j,j} & M_{j,j+1} & ... & M_{j,N^2k} \\ M_{j+1,1} & ... & M_{j+1,j} & M_{j+1,j+1} & ... & M_{j+1,N^2k} \\ ... & ... & ... & ... & ... & ... \\ M_{N^2k,1} & ... & M_{N^2k,j} & M_{N^2k,j+1} & ... & M_{N^2k,N^2k} \end{pmatrix} \tag{8}$$

Let $H_j = (M_{j,j+1}, ..., M_{j,N^2k}) \begin{pmatrix} M_{j+1,j+1} & ... & M_{j+1,N^2k} \\ ... & ... & ... \\ M_{N^2k,j+1} & ... & M_{N^2k,N^2k} \end{pmatrix}^{-1}$.

We next construct independent variables τ_j for $j = 1, 2, ..., N^2k$ using standard textbook techniques (e.g. Anderson, 2003; Muirhead 1982).

$$\tau_1 = \gamma_1 + H_1(\gamma_2, \gamma_3, ..., \gamma_{N^2k})' \tag{9}$$

$$\tau_2 = \gamma_2 + H_2(\gamma_3, \gamma_4, ..., \gamma_{N^2k})' \tag{10}$$

$$...$$

$$\tau_{N^2K-1} = \gamma_{N^2k-1} + H_{N^2k-1}\gamma_{N^2k} \tag{11}$$

$$\tau_{N^2K} = \gamma_{N^2k} \tag{12}$$

The joint density of $\tau_1, \tau_2, ..., \tau_{N^2k}$ is

$$N(\tau_1|0, \sigma^2_{\gamma_1})N(\tau_2|0, \sigma^2_{\gamma_2})...N(\tau_{N^2k}|0, \sigma^2_{\gamma_{N^2k}}) \tag{13}$$

where $\sigma^2_{\gamma_j} = M_{j,j} - H_j(M_{j,j+1}, ..., M_{j,N^2k})'$, with $\sigma^2_{\gamma_{N^2k}} = M_{N^2k,N^2k}$. Note that it is computationally feasible to derive $\sigma^2_{\gamma_j}$ when M is sparse.

The Jacobian of transforming $\Gamma \sim N(0, M)$ to (13) is 1. Defining $\eta_j = \tau_j/\lambda_{1,j}$, we can write (13) as

$$N(\eta_1|0, \sigma^2_{\gamma_1}\lambda^{-2}_{1,1})N(\eta_2|0, \sigma^2_{\gamma_2}\lambda^{-2}_{1,2})...N(\eta_{N^2k}|0, \sigma^2_{\gamma_{N^2k}}\lambda^{-2}_{1,N^2k}) \tag{14}$$

Let $f_j(\Gamma) = 2(\eta^2_j)$. Our scale mixture prior in (7) can be rewritten as:

$$\begin{aligned}\pi(\beta|\Sigma, \Gamma, \Lambda_1, \Lambda_2) \propto \prod_{j=1}^{N^2k} \{ & \frac{\sqrt{\lambda_{2,j}}}{\sqrt{2\pi}} exp(-\frac{\lambda_{2,j}}{2}\beta^2_j) \\ & \times \int_0^\infty \frac{1}{\sqrt{2\pi(2\eta^2_j))}} exp[-\frac{\beta^2_j}{2(2\eta^2_j)}]d(2\eta^2_j) \\ & \times \frac{\lambda^2_{1,j}}{2\sigma^2_{\gamma_j}} exp[-\frac{1}{2}\frac{2\eta^2_j}{(\sigma^2_{\gamma_j})/\lambda^2_{1,j}}]\}\end{aligned} \tag{15}$$

Equation (15) shows that the conditional prior for β_j is $N(0, \frac{2\eta^2_j}{2\lambda_{2,j}\eta^2_j+1})$, and the conditional prior for β is

$$\beta|\Gamma, \Sigma, \Lambda_1, \Lambda_2 \sim N(0, D^*_\Gamma) \tag{16}$$

where $D_\Gamma^* = diag([\frac{2\eta_1^2}{2\lambda_{2,1}\eta_1^2+1}, \frac{2\eta_2^2}{2\lambda_{2,2}\eta_2^2+1}, ..., \frac{2\eta_{N^2k}^2}{2\lambda_{2,N^2k}\eta_{N^2k}^2+1}])$. The tightness of the prior for each β_j depends on $\frac{2\eta_j^2}{2\lambda_{2,j}\eta_j^2+1}$. If $\frac{2\eta_j^2}{2\lambda_{2,j}\eta_j^2+1}$ is small, β_j will be shrunk towards zero. If $\frac{2\eta_j^2}{2\lambda_{2,j}\eta_j^2+1}$ is large, the prior for β_j can become quite uninformative.

Priors for Σ, $\lambda_{1,j}^2$ and $\lambda_{2,j}$ can be elicited following standard practice in VAR and Lasso literature. In this paper, we set Wishart prior for Σ^{-1} and Gamma priors for $\lambda_{1,j}^2$ and $\lambda_{2,j}$: $\Sigma^{-1} \sim W(\underline{S}^{-1}, \underline{\nu})$, $\lambda_{1,j}^2 \sim G(\underline{\mu}_{\lambda_{1,j}^2}, \underline{\nu}_{\lambda_{1,j}^2})$, $\lambda_{2,j} \sim G(\underline{\mu}_{\lambda_{2,j}}, \underline{\nu}_{\lambda_{2,j}})$.[1]

We set the prior distribution for γ as Gamma, which exclude *a priori* the point $\gamma = 0$ from the integration range. Finally, we elicit the conditional prior of c as uniformly distributed between the middle 70% ranges of the transition variables.

We adopt relatively uninformative priors for empirical analysis. First, we set the priors for $\lambda_{1,j}^2$ (or λ_1^2) and $\lambda_{2,j}$ (or λ_2) to be $G(1, 0.0001)$ and $G(1, 0.001)$, respectively. Next, we elicit the prior for Σ^{-1} as $W((N-1)I_N, 1)$. Finally, the prior for γ is set to be $G(3, 4)$.

1.2 Posteriors and Gibbs Sampler

The full conditional posterior for β is $\beta \sim N(\overline{\beta}, \overline{V}_\beta)$, where $\overline{V}_\beta = [(I_N \otimes X)^{'})(\Sigma^{-1} \otimes I_{Nk})(I_N \otimes X) + (D_\Gamma^*)^{-1}]^{-1}$, and $\overline{\beta} = \overline{V}_\beta[(I_N \otimes X)^{'}(\Sigma^{-1} \otimes I_{Nk})y]$. The Full conditional posterior for Σ^{-1} is $W(\overline{S}^{-1}, \overline{\nu})$, with $\overline{S}^{-1} = (Y - XB)^{'}(Y - XB) + 2Q^{'}Q + \underline{S}^{-1}$ and $\overline{\nu} = T + 2Nk + \underline{\nu}$, with $vec(Q) = \Gamma$. The Full conditional posterior for $\lambda_{1,j}^2$ is $G(\bar{\mu}_{\lambda_{1,j}}, \bar{\nu}_{\lambda_{1,j}})$, where $\bar{\nu}_{\lambda_{1,j}} = \underline{\nu}_{\lambda_{1,j}} + 2$ and $\bar{\mu}_{\lambda_{1,j}} = \frac{\overline{\nu}_{\lambda_{1,j}}\sigma_j^2\underline{\mu}_{\lambda_{1,j}}}{2\tau_j^2\underline{\mu}_{\lambda_{1,j}} + \underline{\nu}_{\lambda_{1,j}}\sigma_{\gamma_j}^2}$. The Full conditional posterior for $\lambda_{2,j}$ is $G(\bar{\mu}_{\lambda_{2,j}}, \bar{\nu}_{\lambda_{2,j}})$, where $\bar{\nu}_{\lambda_{2,j}} = \underline{\nu}_{\lambda_{2,j}} + 1$ and $\bar{\mu}_{\lambda_{2,j}} = \frac{\underline{\mu}_{\lambda_{2,j}}\bar{\nu}_{\lambda_{2,j}}}{\underline{\nu}_{\lambda_{2,j}} + \underline{\mu}_{\lambda_{2,j}}\beta_j^2}$. Finally the full conditional posterior of $\frac{1}{2\eta_j^2}$ is Inverse Gaussian: $IG(\sqrt{\frac{\lambda_{1,j}^2}{\beta_j^2\sigma_{\gamma_j}^2}}, \frac{\lambda_{1,j}^2}{\sigma_{\gamma_j}^2})$.[2] Γ can not be directly drawn from the posteriors. But it can be recovered in each Gibbs iteration using the draws of $\frac{1}{2\eta_j^2}$ and Σ .

[1] Please refer to Koop (2003), p326, for Gamma distribution, and Zellner (1971), p389, for Wishart distribution.

[2] We adopt the same form of the inverse-Gaussian density used in Park and Casella (2008).

The posterior distributions for the remaining parameters, γ and c, have nonstandard forms. In this paper, we use Metropolis-Hastings algorithm (Chib and Greenberg, 1995) within Gibbs to estimate γ and c.

Conditional on arbitrary starting values, the Gibbs sampler contains the following seven steps:

1. draw $\beta|\Sigma, \Lambda_1, \Lambda_2, \Gamma, \gamma, c$ from $N(\overline{\beta}, \overline{V}_\beta)$;
2. draw $\Sigma^{-1}|\beta, \Lambda_1, \Lambda_2, \Gamma, \gamma, c$ from $W(\overline{S}^{-1}, \overline{\nu})$
3. draw $\lambda_{1,j}^2|\beta, \Sigma, \Lambda_{1,-j}, \Lambda_2, \Gamma, \gamma, c$ from $G(\bar{\mu}_{\lambda_{1,j}}, \bar{\nu}_{\lambda_{1,j}})$ for $j = 1, 2, ...N^2k$
4. draw $\lambda_{2,j}|\beta, \Sigma, \Lambda_1, \Lambda_{2,-j}, \Gamma, \gamma, c$ from $G(\bar{\mu}_{\lambda_{2,j}}, \bar{\nu}_{\lambda_{2,j}})$ for $j = 1, 2, ...N^2k$
5. draw $\frac{1}{2\eta_j^2}|\beta, \Sigma, \Lambda_1, \Lambda_2, \gamma, c$ from $IG(\sqrt{\frac{\lambda_{1,j}^2}{\beta_j^2\sigma_{\gamma_j}^2}}, \frac{\lambda_{1,j}^2}{\sigma_{\gamma_j}^2})$ for $j = 1, 2, ...N^2k$.
6. calculate Γ based on draws of Σ and $\frac{1}{2\eta_j^2}$ in the current iteration.
7. draw γ and c conditional on other parameters using Metropolis-Hastings algorithm

2 Generalized Spillover Measure

When $z_t = z_\tau$, model (1) can be written as:

$$y_t = (\Phi + \Phi^z F(z_\tau)) + \Sigma_{h=1}^p (\Gamma_h + \Gamma_h^z F(z_\tau))\, y_{t-h} + \varepsilon_t \tag{17}$$

Let $\Psi_h = \Gamma_h + \Gamma_h^z F(z_\tau)$. Following Diebold and Yilmaz (2012), we write equation (17) in its moving average representation:

$$y_t = \mu + \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \tag{18}$$

where μ is the mean, and the moving average coefficients A_i can be computed recursively using $A_0 = I_N$, and $A_i = \sum_{j=1}^{i} A_{i-j}\Psi_j$.

The H-step-ahead forecast error variance decompositions is

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)} \tag{19}$$

where σ_{jj} is the standard deviation of the error terms for the j^{th} equation, and e^i is the selection vector with one as the i^{th} element and 0s otherwise.

Next, we normalize each row of the variance decomposition matrix by the following:

$$\widetilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{20}$$

The directional spillovers received by the variable i from all other variables is defined as

$$S_{i.}^{g}(H) = \frac{\sum_{j=1;j\neq i}^{N} \widetilde{\theta}_{ij}^{g}(H)}{N/100} \tag{21}$$

The directional spillovers transmitted by the variable i to all other variables is defined as

$$S_{.i}^{g}(H) = \frac{\sum_{j=1;j\neq i}^{N} \widetilde{\theta}_{ji}^{g}(H)}{N/100} \tag{22}$$

Finally, the net pairwise spillovers is defined as

$$S_{ij}^{g}(H) = \frac{\widetilde{\theta}_{ji}^{g}(H) - \widetilde{\theta}_{ij}^{g}(H)}{N/100} \tag{23}$$

3 Prior Sensitivity Analysis

Our empirical results are relatively robust to the prior choices. In this section, we report the spillover measures for the most preferred model, LSTVAR(2) with the lagged 4 quarters consumer confidence level as transition variables, using the following priors: $\lambda_{1,j}^2 \sim G(1, 0.0001)$, $\lambda_{2,j} \sim G(1, 0.0001)$, $\Sigma^{-1} \sim W(9 * I_N, 1)$ and $\gamma \sim G(1, 1)$.

Table 1: Directional Spillover From Others

Variable	Region	Lower Regime h=2	Lower Regime h=4	Middle Regime h=2	Middle Regime h=4	Upper Regime h=2	Upper Regime h=4
	NE	0.9698	0.9693	0.9692	0.9696	0.9700	0.9712
	NW	0.9688	0.9663	0.9697	0.9683	0.9684	0.9701
	Y & H	0.9732	0.9674	0.9673	0.9657	0.9613	0.9658
	EM	0.9759	0.9706	0.9762	0.9709	0.9762	0.9691
	WM	0.9769	0.9749	0.9744	0.9717	0.9699	0.9668
s	East	0.9543	0.9621	0.9533	0.9622	0.9564	0.9663
	London	0.9745	0.9762	0.9721	0.9743	0.9704	0.9714
	SE	0.9706	0.9688	0.9734	0.9710	0.9737	0.9710
	SW	0.9747	0.9720	0.9735	0.9690	0.9701	0.9670
	Wales	0.9695	0.9677	0.9659	0.9647	0.9667	0.9626
	Scotland	0.9708	0.9687	0.9689	0.9657	0.9674	0.9670
	NE	0.9585	0.9574	0.9611	0.9595	0.9668	0.9674
	NW	0.9610	0.9616	0.9668	0.9672	0.9710	0.9694
	Y & H	0.9705	0.9689	0.9637	0.9667	0.9597	0.9677
	EM	0.9731	0.9701	0.9702	0.9704	0.9681	0.9717
	WM	0.9778	0.9745	0.9761	0.9738	0.9732	0.9712
f	East	0.9726	0.9708	0.9720	0.9711	0.9720	0.9722
	London	0.9683	0.9669	0.9656	0.9660	0.9650	0.9651
	SE	0.9726	0.9674	0.9704	0.9678	0.9669	0.9655
	SW	0.9652	0.9629	0.9692	0.9668	0.9709	0.9685
	Wales	0.9769	0.9718	0.9784	0.9742	0.9760	0.9703
	Scotland	0.9610	0.9641	0.9571	0.9641	0.9565	0.9624
	NE	0.9756	0.9701	0.9680	0.9664	0.9632	0.9676
	NW	0.9490	0.9581	0.9560	0.9680	0.9681	0.9737
	Y & H	0.9742	0.9719	0.9748	0.9704	0.9711	0.9683
	EM	0.9703	0.9697	0.9659	0.9711	0.9651	0.9692
	WM	0.9719	0.9729	0.9745	0.9735	0.9708	0.9687
v	East	0.9576	0.9652	0.9598	0.9672	0.9633	0.9664
	London	0.9560	0.9657	0.9584	0.9662	0.9649	0.9720
	SE	0.9716	0.9717	0.9783	0.9759	0.9805	0.9729
	SW	0.9531	0.9624	0.9558	0.9646	0.9655	0.9731
	Wales	0.9763	0.9744	0.9832	0.9770	0.9817	0.9718
	Scotland	0.9728	0.9719	0.9741	0.9732	0.9726	0.9712

Notes:

We use s to denote inflow rate, f to denote outflow rate and v to denote vacancy rate.

Table 2: Directional Spillover To Others

Variable	Region	Lower Regime h=2	Lower Regime h=4	Middle Regime h=2	Middle Regime h=4	Upper Regime h=2	Upper Regime h=4
	NE	1.0269	1.0033	0.9927	1.0019	0.9438	0.9660
	NW	1.0534	1.0717	1.0237	1.0228	1.0332	1.0018
	Y & H	0.9718	0.9928	1.0209	1.0295	1.0479	1.0553
	EM	1.0598	1.0654	0.9645	0.9706	0.8850	0.9053
	WM	0.8180	0.8315	0.8698	0.9048	0.9547	1.0063
s	East	1.0714	1.0564	1.0584	1.0233	1.0464	0.9994
	London	0.9079	0.8786	0.8858	0.8682	0.8925	0.8761
	SE	0.9290	0.9146	0.9059	0.9245	0.8967	0.9262
	SW	0.8991	0.8882	0.8893	0.9005	0.9309	0.9569
	Wales	1.1219	1.1056	1.1546	1.1549	1.1253	1.1213
	Scotland	1.1207	1.1070	1.1480	1.1744	1.1075	1.1247
	NE	1.1085	1.1378	1.0853	1.1305	0.9857	1.0297
	NW	1.0127	1.0436	1.0748	1.0916	1.0420	1.0169
	Y & H	0.9878	1.0174	1.0491	1.0704	1.0948	1.0838
	EM	0.9762	0.9819	0.9677	0.9650	0.9554	0.9456
	WM	0.8899	0.8819	0.8966	0.9046	0.8824	0.8930
f	East	0.9554	0.9633	0.9520	0.9702	0.9299	0.9389
	London	1.0007	1.0006	0.9857	1.0123	0.9462	0.9741
	SE	0.9872	0.9971	1.0914	1.1074	1.2132	1.2206
	SW	1.0836	1.1185	1.0232	1.0544	0.9818	1.0114
	Wales	0.9479	0.9626	0.8956	0.9394	0.9024	0.9492
	Scotland	0.9989	1.0042	1.0308	1.0461	0.9939	1.0103
	NE	0.8615	0.8359	0.9046	0.8463	0.9439	0.9067
	NW	0.9266	0.9311	0.8327	0.8144	0.8032	0.7929
	Y & H	0.9074	0.9069	0.9154	0.9025	0.9662	0.9483
	EM	0.9440	0.9520	0.9766	0.9567	1.0042	1.0092
	WM	0.8358	0.8321	0.8816	0.8932	0.9281	0.9475
v	East	1.0033	0.9915	1.0137	0.9708	1.0923	1.0460
	London	0.8207	0.8168	0.7474	0.7416	0.7340	0.7245
	SE	0.9160	0.9068	0.8873	0.8935	0.8718	0.8998
	SW	0.7888	0.7978	0.7819	0.7854	0.8098	0.8096
	Wales	0.9834	0.9439	1.0304	0.8999	1.0348	0.9105
	Scotland	1.0483	1.0150	1.0261	1.0021	0.9837	0.9664

Notes:

We use s to denote inflow rate, f to denote outflow rate and v to denote vacancy rate.

Table 3: Net Spillover To All Other Variables

Variable	Region	Lower Regime h=2	Lower Regime h=4	Middle Regime h=2	Middle Regime h=4	Upper Regime h=2	Upper Regime h=4
	NE	0.0571	0.0340	0.0235	0.0323	-0.0262	-0.0051
	NW	0.0846	0.1055	0.0539	0.0545	0.0648	0.0317
	Y & H	-0.0013	0.0255	0.0536	0.0638	0.0866	0.0895
	EM	0.0839	0.0948	-0.0118	-0.0004	-0.0912	-0.0638
	WM	-0.1588	-0.1435	-0.1046	-0.0669	-0.0152	0.0394
s	East	0.1170	0.0942	0.1051	0.0612	0.0899	0.0331
	London	-0.0666	-0.0977	-0.0863	-0.1061	-0.0779	-0.0952
	SE	-0.0415	-0.0542	-0.0676	-0.0465	-0.0770	-0.0448
	SW	-0.0756	-0.0838	-0.0841	-0.0685	-0.0392	-0.0101
	Wales	0.1524	0.1379	0.1887	0.1902	0.1586	0.1587
	Scotland	0.1499	0.1383	0.1791	0.2087	0.1401	0.1577
	NE	0.1500	0.1804	0.1241	0.1710	0.0189	0.0623
	NW	0.0518	0.0820	0.1080	0.1244	0.0711	0.0475
	Y & H	0.0174	0.0485	0.0855	0.1037	0.1351	0.1161
	EM	0.0031	0.0118	-0.0025	-0.0054	-0.0127	-0.0260
	WM	-0.0879	-0.0925	-0.0795	-0.0691	-0.0908	-0.0782
f	East	-0.0172	-0.0075	-0.0199	-0.0009	-0.0421	-0.0333
	London	0.0324	0.0337	0.0201	0.0463	-0.0188	0.0090
	SE	0.0146	0.0298	0.1210	0.1397	0.2463	0.2551
	SW	0.1184	0.1556	0.0540	0.0876	0.0109	0.0429
	Wales	-0.0289	-0.0092	-0.0829	-0.0348	-0.0736	-0.0211
	Scotland	0.0379	0.0401	0.0736	0.0819	0.0373	0.0480
	NE	-0.1141	-0.1342	-0.0634	-0.1200	-0.0194	-0.0609
	NW	-0.0224	-0.0270	-0.1233	-0.1536	-0.1649	-0.1808
	Y & H	-0.0668	-0.0650	-0.0594	-0.0679	-0.0050	-0.0199
	EM	-0.0263	-0.0176	0.0107	-0.0144	0.0391	0.0400
	WM	-0.1361	-0.1408	-0.0930	-0.0803	-0.0427	-0.0212
v	East	0.0457	0.0263	0.0539	0.0036	0.1289	0.0796
	London	-0.1353	-0.1489	-0.2110	-0.2247	-0.2309	-0.2474
	SE	-0.0555	-0.0649	-0.0910	-0.0824	-0.1087	-0.0731
	SW	-0.1643	-0.1645	-0.1740	-0.1791	-0.1557	-0.1635
	Wales	0.0071	-0.0306	0.0472	-0.0771	0.0531	-0.0613
	Scotland	0.0756	0.0430	0.0520	0.0289	0.0111	-0.0048

Notes:

We use s to denote inflow rate, f to denote outflow rate and v to denote vacancy rate.

Table 4: Net Spillovers From Each Regional Inflows To Inflows Of All Other Regions

Region	Lower Regime h=2	Lower Regime h=4	Middle Regime h=2	Middle Regime h=4	Upper Regime h=2	Upper Regime h=4
NE	0.0149	-0.0050	0.0064	-0.0025	-0.0254	-0.0140
NW	-0.0019	0.0153	0.0093	0.0015	0.0250	0.0033
Y & H	-0.0281	-0.0063	-0.0216	-0.0002	-0.0084	0.0067
EM	0.0469	0.0495	-0.0052	0.0029	-0.0442	-0.0184
WM	-0.0933	-0.0673	-0.0616	-0.0395	-0.0236	-0.0043
East	0.0086	0.0094	0.0204	0.0045	0.0273	-0.0029
London	0.0435	-0.0115	0.0469	-0.0241	0.0358	-0.0301
SE	0.0097	-0.0164	-0.0013	-0.0126	-0.0153	-0.0160
SW	0.0029	-0.0209	-0.0178	-0.0221	-0.0163	-0.0073
Wales	-0.0043	0.0269	0.0100	0.0402	0.0250	0.0389
Scotland	0.0012	0.0262	0.0144	0.0520	0.0201	0.0440

Table 5: Net Spillovers From Each Regional Inflows To Outflows Of All Regions

Region	Lower Regime h=2	Lower Regime h=4	Middle Regime h=2	Middle Regime h=4	Upper Regime h=2	Upper Regime h=4
NE	0.0469	0.0172	0.0327	0.0227	0.0064	-0.0036
NW	0.0278	0.0279	0.0058	-0.0042	0.0130	-0.0044
Y & H	-0.0167	-0.0086	-0.0212	-0.0007	-0.0046	0.0235
EM	-0.0627	-0.0273	-0.0784	-0.0487	-0.0652	-0.0513
WM	-0.0598	-0.0535	-0.0580	-0.0370	-0.0193	0.0063
East	0.0404	0.0256	0.0286	0.0068	0.0206	0.0045
London	-0.0693	-0.0712	-0.0895	-0.0835	-0.0797	-0.0543
SE	-0.0279	-0.0359	-0.0387	-0.0421	-0.0352	-0.0370
SW	-0.0190	-0.0351	-0.0185	-0.0361	-0.0164	-0.0102
Wales	0.0799	0.0364	0.1105	0.0649	0.0873	0.0567
Scotland	0.0811	0.0309	0.1004	0.0577	0.0681	0.0436

Table 6: Net Spillovers From Each Regional Inflows To Vacancies Of All Regions

Region	Lower Regime h=2	Lower Regime h=4	Middle Regime h=2	Middle Regime h=4	Upper Regime h=2	Upper Regime h=4
NE	-0.0047	0.0218	-0.0157	0.0121	-0.0072	0.0124
NW	0.0587	0.0623	0.0388	0.0572	0.0268	0.0328
Y & H	0.0435	0.0404	0.0964	0.0647	0.0996	0.0593
EM	0.0997	0.0726	0.0718	0.0455	0.0182	0.0060
WM	-0.0057	-0.0226	0.0149	0.0096	0.0277	0.0374
East	0.0681	0.0592	0.0561	0.0498	0.0420	0.0314
London	-0.0408	-0.0149	-0.0437	0.0016	-0.0340	-0.0108
SE	-0.0233	-0.0019	-0.0276	0.0081	-0.0265	0.0083
SW	-0.0596	-0.0279	-0.0478	-0.0103	-0.0065	0.0074
Wales	0.0768	0.0746	0.0682	0.0852	0.0463	0.0631
Scotland	0.0676	0.0812	0.0643	0.0990	0.0520	0.0701

Table 7: Net Spillover From Each Regional Outflows To Outflows Of All Other Regions

Region	Lower Regime h=2	Lower Regime h=4	Middle Regime h=2	Middle Regime h=4	Upper Regime h=2	Upper Regime h=4
NE	0.0190	0.0314	0.0143	0.0319	-0.0111	0.0057
NW	-0.0194	-0.0078	-0.0173	-0.0085	-0.0111	-0.0113
Y & H	0.0264	0.0145	0.0313	0.0113	0.0318	0.0226
EM	0.0142	0.0077	0.0131	-0.0011	0.0048	-0.0150
WM	-0.0439	-0.0412	-0.0416	-0.0380	-0.0413	-0.0378
East	-0.0193	-0.0227	-0.0197	-0.0245	-0.0235	-0.0295
London	-0.0120	-0.0020	-0.0340	-0.0232	-0.0377	-0.0173
SE	0.0351	0.0013	0.0764	0.0487	0.1042	0.0833
SW	0.0004	0.0197	-0.0446	-0.0112	-0.0422	-0.0068
Wales	-0.0008	-0.0081	-0.0022	0.0031	0.0011	0.0071
Scotland	0.0003	0.0072	0.0243	0.0114	0.0250	-0.0010

Table 8: Net Spillover From Each Regional Outflows To Inflows Of All Regions

Region	Lower Regime h=2	Lower Regime h=4	Middle Regime h=2	Middle Regime h=4	Upper Regime h=2	Upper Regime h=4
NE	0.1010	0.1018	0.0716	0.0781	0.0175	0.0155
NW	0.0677	0.0605	0.0993	0.0784	0.0672	0.0331
Y & H	-0.0227	0.0067	0.0189	0.0350	0.0468	0.0255
EM	-0.0352	-0.0193	-0.0500	-0.0245	-0.0444	-0.0192
WM	-0.0472	-0.0525	-0.0448	-0.0479	-0.0468	-0.0449
East	-0.0137	-0.0081	-0.0145	-0.0156	-0.0134	-0.0197
London	-0.0365	-0.0156	-0.0465	-0.0116	-0.0472	-0.0124
SE	-0.0220	-0.0017	0.0187	0.0222	0.0824	0.0745
SW	0.0102	0.0418	0.0031	0.0175	-0.0057	0.0035
Wales	-0.0134	-0.0084	-0.0304	-0.0287	-0.0219	-0.0280
Scotland	-0.0090	-0.0116	0.0011	-0.0028	-0.0094	-0.0016

Table 9: Net Spillover From Each Regional Outflows To Vacancies Of All Regions

Region	Lower Regime h=2	Lower Regime h=4	Middle Regime h=2	Middle Regime h=4	Upper Regime h=2	Upper Regime h=4
NE	0.0299	0.0472	0.0383	0.0610	0.0125	0.0411
NW	0.0035	0.0293	0.0260	0.0544	0.0149	0.0257
Y & H	0.0137	0.0274	0.0353	0.0574	0.0566	0.0680
EM	0.0242	0.0235	0.0344	0.0202	0.0269	0.0081
WM	0.0031	0.0012	0.0069	0.0168	-0.0027	0.0045
East	0.0157	0.0233	0.0143	0.0392	-0.0052	0.0159
London	0.0810	0.0513	0.1006	0.0812	0.0661	0.0387
SE	0.0016	0.0302	0.0259	0.0687	0.0598	0.0973
SW	0.1077	0.0941	0.0955	0.0813	0.0588	0.0462
Wales	-0.0148	0.0073	-0.0502	-0.0092	-0.0528	-0.0002
Scotland	0.0466	0.0445	0.0482	0.0732	0.0217	0.0506

Table 10: Net Spillover From Each Regional Vacancies To Vacancies Of All Other Regions

Region	Lower Regime h=2	Lower Regime h=4	Middle Regime h=2	Middle Regime h=4	Upper Regime h=2	Upper Regime h=4
NE	-0.0211	-0.0304	0.0212	-0.0177	0.0328	-0.0085
NW	0.0169	0.0054	-0.0050	-0.0127	-0.0224	-0.0184
Y & H	-0.0287	-0.0087	-0.0266	-0.0052	-0.0012	0.0049
EM	0.0266	0.0311	0.0425	0.0366	0.0367	0.0449
WM	-0.0304	-0.0292	-0.0193	-0.0072	-0.0049	0.0083
East	0.0420	0.0398	0.0299	0.0324	0.0513	0.0407
London	-0.0474	-0.0354	-0.0619	-0.0380	-0.0787	-0.0505
SE	-0.0155	-0.0044	-0.0294	-0.0013	-0.0297	-0.0015
SW	-0.0331	-0.0313	-0.0283	-0.0284	-0.0256	-0.0280
Wales	0.0187	0.0112	0.0129	0.0055	0.0069	0.0008
Scotland	0.0720	0.0519	0.0640	0.0361	0.0348	0.0074

Table 11: Net Spillover From Each Regional Vacancies To Inflows Of All Regions

Region	Lower Regime h=2	Lower Regime h=4	Middle Regime h=2	Middle Regime h=4	Upper Regime h=2	Upper Regime h=4
NE	-0.0436	-0.0467	-0.0320	-0.0394	-0.0134	-0.0147
NW	-0.0040	-0.0105	-0.0588	-0.0763	-0.0824	-0.0850
Y & H	0.0000	-0.0244	-0.0074	-0.0342	-0.0064	-0.0171
EM	-0.0218	-0.0254	0.0033	-0.0090	0.0175	0.0127
WM	-0.0702	-0.0712	-0.0769	-0.0524	-0.0594	-0.0213
East	0.0308	0.0116	0.0343	0.0043	0.0430	0.0186
London	-0.0626	-0.0667	-0.0818	-0.0874	-0.0806	-0.0956
SE	-0.0322	-0.0318	-0.0486	-0.0305	-0.0574	-0.0207
SW	-0.0518	-0.0601	-0.0580	-0.0763	-0.0557	-0.0745
Wales	-0.0468	-0.0324	0.0055	-0.0459	0.0314	-0.0299
Scotland	0.0219	0.0127	0.0447	0.0246	0.0249	0.0104

Table 12: Net Spillover From Each Regional Vacancies To Outflows Of All Regions

Region	Lower Regime h=2	Lower Regime h=4	Middle Regime h=2	Middle Regime h=4	Upper Regime h=2	Upper Regime h=4
NE	-0.0495	-0.0571	-0.0525	-0.0629	-0.0388	-0.0376
NW	-0.0353	-0.0219	-0.0595	-0.0645	-0.0601	-0.0774
Y & H	-0.0381	-0.0319	-0.0253	-0.0285	0.0026	-0.0077
EM	-0.0311	-0.0234	-0.0351	-0.0420	-0.0151	-0.0176
WM	-0.0356	-0.0404	0.0032	-0.0207	0.0215	-0.0081
East	-0.0271	-0.0252	-0.0103	-0.0331	0.0346	0.0204
London	-0.0254	-0.0468	-0.0673	-0.0992	-0.0716	-0.1013
SE	-0.0078	-0.0286	-0.0130	-0.0506	-0.0217	-0.0508
SW	-0.0793	-0.0732	-0.0877	-0.0744	-0.0744	-0.0610
Wales	0.0352	-0.0093	0.0289	-0.0366	0.0147	-0.0322
Scotland	-0.0184	-0.0216	-0.0567	-0.0317	-0.0485	-0.0225

Table 13: Net Spillovers Within Regions, Lower Regime

	Region	Inflow Rate	Outflow Rate	Vacancy Rate
	NE	-0.0060	0.0107	-0.0046
	NW	0.0108	0.0048	-0.0156
	Y & H	-0.0032	0.0155	-0.0123
	EM	-0.0005	0.0082	-0.0077
	WM	-0.0047	-0.0062	0.0109
$h = 2$	East	0.0509	-0.0250	-0.0259
	London	-0.0007	-0.0092	0.0099
	SE	0.0122	0.0029	-0.0151
	SW	-0.0067	0.0155	-0.0087
	Wales	0.0309	-0.0583	0.0274
	Scotland	0.0185	-0.0154	-0.0031
	NE	-0.0024	0.0096	-0.0072
	NW	0.0043	0.0027	-0.0070
	Y & H	-0.0001	0.0054	-0.0052
	EM	0.0055	-0.0001	-0.0054
	WM	-0.0002	0.0013	-0.0010
$h = 4$	East	0.0217	-0.0108	-0.0109
	London	-0.0034	0.0056	-0.0021
	SE	0.0017	0.0093	-0.0110
	SW	-0.0072	0.0175	-0.0103
	Wales	0.0191	-0.0252	0.0061
	Scotland	0.0119	-0.0060	-0.0059

Table 14: Net Spillovers Within Regions, Middle Regime

	Region	Inflow Rate	Outflow Rate	Vacancy Rate
	NE	-0.0124	0.0110	0.0014
	NW	0.0130	0.0175	-0.0305
	Y & H	-0.0148	0.0388	-0.0239
	EM	-0.0069	0.0204	-0.0134
	WM	-0.0039	-0.0083	0.0122
$h = 2$	East	0.0461	-0.0131	-0.0329
	London	-0.0053	0.0068	-0.0015
	SE	0.0012	0.0281	-0.0293
	SW	-0.0064	0.0146	-0.0082
	Wales	0.0188	-0.0660	0.0472
	Scotland	0.0159	-0.0031	-0.0128
	NE	-0.0050	0.0077	-0.0028
	NW	0.0055	0.0149	-0.0204
	Y & H	-0.0021	0.0130	-0.0109
	EM	0.0000	0.0067	-0.0066
	WM	-0.0009	-0.0022	0.0031
$h = 4$	East	0.0184	-0.0015	-0.0169
	London	-0.0001	0.0137	-0.0136
	SE	-0.0057	0.0228	-0.0171
	SW	-0.0038	0.0116	-0.0077
	Wales	0.0189	-0.0258	0.0069
	Scotland	0.0136	-0.0001	-0.0134

Table 15: Net Spillovers Within Regions, Upper Regime

	Region	Inflow Rate	Outflow Rate	Vacancy Rate
	NE	-0.0120	0.0082	0.0038
	NW	0.0122	0.0128	-0.0251
	Y & H	-0.0181	0.0410	-0.0229
	EM	-0.0128	0.0207	-0.0079
	WM	0.0002	-0.0098	0.0096
$h = 2$	East	0.0200	-0.0082	-0.0118
	London	-0.0062	0.0126	-0.0064
	SE	-0.0115	0.0414	-0.0299
	SW	0.0034	0.0075	-0.0109
	Wales	0.0079	-0.0481	0.0401
	Scotland	0.0160	-0.0024	-0.0137
	NE	-0.0043	0.0042	0.0001
	NW	0.0029	0.0135	-0.0165
	Y & H	0.0038	0.0044	-0.0082
	EM	-0.0076	0.0028	0.0048
	WM	0.0050	-0.0084	0.0034
$h = 4$	East	0.0025	-0.0025	0.0000
	London	0.0067	0.0111	-0.0178
	SE	-0.0079	0.0225	-0.0146
	SW	0.0037	0.0042	-0.0079
	Wales	0.0165	-0.0144	-0.0021
	Scotland	0.0087	-0.0013	-0.0073

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