Business Cycle Characteristics of the Australian Labour Market with an Endogenous Participation Rate

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Abstract

We use a SVAR model to analyse gross flows of workers between the states of employment, unemployment and non-participation in the Australian labour market. We determine the cyclicality of stocks, gross flows and state transition rates by examining their responses to business cycle shocks. We use the derived cyclicality of transition rates to characterise labour force inflows and outflows as being consistent in aggregate with either the Discouraged-Worker Effect or the Added-Worker Effect. We find evidence that the total participation rate is procyclical which means that the Discouraged-Worker Effect is dominant overall, but also find that the Added-Worker Effect is dominant in several particular types of transition. We also apply shocks to gross flows between employment and unemployment and find that unemployment inflows are more important than outflows to the evolution of the unemployment rate. We find that participation decisions make only a small contribution to unemployment relative to flows between employment and unemployment.

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Declaration of Originality

I declare that this thesis is my own work and has not been submitted in any form for another degree or diploma at any university or other institute of tertiary education. Information derived from the published and unpublished work of others has been acknowledged in the text and in the list of references.

Andrew Evans

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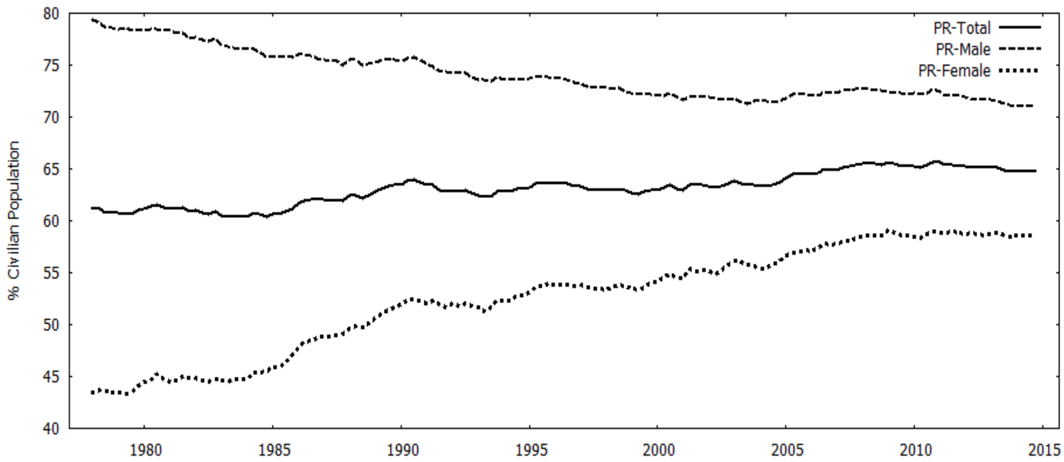
1. Introduction

The last four decades have seen profound changes in the labour force participation rate both in Australia and internationally. The most obvious trends in the Australian data over this period have been the increase in female participation and overall participation and a steady decline in male participation as illustrated in Figure 1. These trends have been attributed in part to changing social attitudes towards the role of women in the workforce and in home production, the levels of educational attainment for both genders and a change in the prevalence of part-time and casual working hours. Detailed studies of trend changes in the composition of the workforce in Australia can be found in Wilkins and Wooden (2014) and Borland and Kennedy (1998). Autor (2010) and Moffitt (2012) provide comprehensive studies of trends in United States labour force participation.

Figure 1. Participation rates in Australia



Source: Australian Bureau of Statistics (ABS) Catalogue 6202, seasonally adj. participation rates by sex.

Australia witnessed a possible reversal in the trend in participation rates at around the time of the global financial crisis in 2008. Total participation started to decline after the crisis and a similar effect has been noted in other developed economies such as the United States (Erceg & Levin, 2014). It is not obvious whether these observations are indeed reflective of a trend change as opposed to a business cycle effect prompted by the intensity of the financial crisis. A pertinent question is whether declining participation has masked so-called hidden unemployment due to discouraged workers moving from unemployment to non-participation. Hotchkiss and Rios-Avila (2013) found evidence that the sharp decline in participation in the United States following the global financial crisis could be explained by cyclical factors. However they also found evidence of an ongoing demographic trend which will continue to reduce the level of participation in coming years. Erceg and Levin (2014) found that cyclical factors accounted for the bulk of the decline in United States labour force participation post-2007. However they also found that the cyclical response of the participation rate was highly asymmetric, showing a marked drop only in the wake of a large and persistent decline in aggregate demand. That being so, the standard measure of the unemployment rate (which ignores participation) could be considered an inadequate indicator of labour market slack and they argued that this could have crucial implications for the design of monetary policy. This highlights the need to differentiate between trend and business cycle components of the participation rate particularly in framing policy responses aimed at retaining or increasing participation.

Examination of the behaviour of the stocks of unemployed and non-participating workers requires an understanding of the inflows to and outflows from each pool of workers. An ideal model of the labour market would explain variation in both stocks and flows. Jones and Riddell (1999) found evidence in the United States that the flow of marginally attached workers returning to the labour force via the unemployment pool during an economic recovery increased the persistence of the measured rate of unemployment. Kudlyak and Schwartzman (2012) analysed state transition probabilities and found that flows to and from non-participation accounted for a significant part of the persistence of unemployment in the recovery period after a recession. Worker flow data also allows the examination of the business cycle behaviour of particular transition probabilities that are of wide interest in research such as the job-finding and job-separation probabilities and the probabilities of transitioning into or out of the labour force. Notable works in this field include Hall (2005) and Shimer (2012).

This research report will determine whether there is significant evidence of a business cycle component in the dynamics of the Australian labour force participation rate. Short-run policy initiatives directed towards increasing the participation rate can only be made effective if we understand the interaction between participation decisions and the unemployment rate during the business cycle. This research may also assist policy formulation by suggesting the appropriate weight that should be given to alternative government programs that seek either to assist job creation or to protect existing jobs, which has been considered by other authors including Barnichon and Figura (2012, p. 5).

Empirical observations of many economies reveal that changes in unemployment and other labour market variables tend to be highly persistent. A VAR framework is therefore a natural choice for an empirical model that seeks to capture persistent interaction between the variables. Persistence is likely to be a manifestation of underlying frictions or imperfections in the labour market since, without them, unemployment would return quickly to its natural rate according to modern theory. So we also consider whether a search and matching framework using the level of job vacancies as well as the flow data can make a useful contribution to explaining the observed persistence in labour market variables.

In section 2 we discuss cyclicality of the participation rate and two theories which have been put forward to help explain it, in the form of the Added-Worker Effect and the Discouraged-Worker Effect. Section 3 describes the empirical data to be examined, including necessary transformations of gross flow data to make it compatible with stock data. The section also introduces the methodology for calculating flow-rates and includes preliminary analysis of the business cycle characteristics of key data series. In section 4 we examine the possibility of a long term relationship between unemployment and vacancy rates using an approach suggested by search and matching theory. In section 5 we set up a SVAR model using a mixture of gross flows, labour market stocks and vacancies to examine the responses of key variables to business cycle shocks and shocks to particular gross flows. Section 6 provides the empirical results derived using the SVAR model and in section 7 we conclude.

2. Cyclicality of labour force participation

Two prominent theories that have been put forward to explain cyclical movement of people to and from the labour force are the so-called Added-Worker Effect and the Discouraged-Worker Effect (Mincer, 1966). The Added-Worker Effect ('AWE') is a theory that when a person loses their job other family or household members are motivated to join the workforce to try and make up for the loss of household income. This effect contributes to an increase in labour force participation in a recession. Sometimes the effect can be defined narrowly, for example, it can be defined to relate only to the added supply of labour by a woman whose male spouse has recently lost his job, as considered by Stephens (2002). The effect can be defined more generally to include any situation where there is smoothing of household income due to an increase in the labour supply of the household in response to the reduction of other household member's incomes. In the general case the AWE is expected to contribute to countercyclical fluctuations in labour force participation. The so-called Discouraged-Worker Effect ('DWE') works in the opposite direction. This theory posits that some unemployed workers become so discouraged at the prospect of finding a job in an economic downturn that they stop searching for work and therefore become classified as non-participating rather than unemployed. Once again it is possible to consider narrow or broad definitions of the effect. A narrow definition may only consider movement of workers who have been classified in a labour force survey as *wanting* work but who are not searching because they do not believe they can find work. Sometimes discussion of the effect is confined to so-called secondary workers who do not provide the primary household income and who only consider joining the workforce when employment prospects are buoyant. Secondary workers may contribute a substantial portion of the movement of discouraged workers (Benati, 2001; Blanchard & Diamond, 1990). A broader definition of DWE would include any tendency for a net outflow from the labour force in recessions and a net inflow in subsequent economic recoveries, i.e. procyclical labour force participation[1].

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[1] In this paper procyclicality of a time series means a tendency of the series to rise during the growth phase of an economic cycle and to decline in the contraction phase.

For clarity we note that the terms AWE and DWE were originally coined in the context of the micro-behaviour of specific groups of workers in particular circumstances. In more general use they may simply mean the behaviour of aggregate labour force participation at a business cycle frequency, as in Benati (2001, p. 388). Empirical evidence of procyclical participation may be interpreted as evidence that DWE dominates AWE, and vice versa if there is evidence that participation is countercyclical, as in Congregado, Golpe and van Stel (2011). We will adopt the more general meaning of AWE and DWE in this paper.

Mincer (1966, p. 74) emphasised that the AWE and DWE should not be held as opposing theories since they can co-exist. The difficulty for analysis is that aggregate data can only reveal which of the opposing effects is dominant but cannot necessarily reveal the contribution which each makes to the net effect. Mincer (1966, p. 100) found empirical evidence for a net DWE amongst the secondary workforce and evidence of the AWE amongst low-income subgroups. There have been numerous studies since Mincer which have attempted to find empirical support for both effects, of which we mention only a small number. Stephens (2002) uses data from a United States panel study to find evidence of the AWE in the narrow category of wives of men who have recently lost their job. Gong (2011) similarly finds evidence of the AWE for married women in Australia in the form of increased full-time employment and increased working hours. Benati (2001) finds evidence of net behaviour dominated by the DWE in United States for the whole and certain subgroups of non-participants, i.e. non-participants who look for jobs only when they think they are available and who give up looking during recessions. Borland (2009) examines Australian labour force participation with the economy in recession or emerging from it. He finds that females joining the workforce during a recovery offset the growth in employment to some extent and *reduce* the decline of the unemployment rate[2] in recoveries, whilst male workers leaving the workforce

[2] This is the conventional measure of the unemployment rate as a percentage of the labour force.

during recessions make a small contribution to reducing unemployment. Both of these findings by Borland are consistent with a net DWE[3].

In relation to the United States labour market there is no consensus on the cyclicality of the participation rate. Benati (2001) finds clear evidence of counter-cyclicality in groups of non-participants (procyclical participation rate) but notes that major studies stretching back several decades have been split between findings of no cyclicality, pro-cyclicality and counter-cyclicality. Yashiv (2007) finds broad agreement between various authors for pro-cyclicality of flows between out-of-the-labour-force and employment but notes that there are ongoing disagreements about how such flows should be measured. Barnichon and Figura (2012, p. 3) claim that in recessions unemployed individuals are more likely to remain in the labour force and that inactive individuals are more likely to join it (both of which are consistent with AWE). On the other hand Haefke and Reiter (2006) appeal to the intuition that 'a large number of people join the labour force in booms when expected wages are high' (p. 1) which is consistent with DWE.

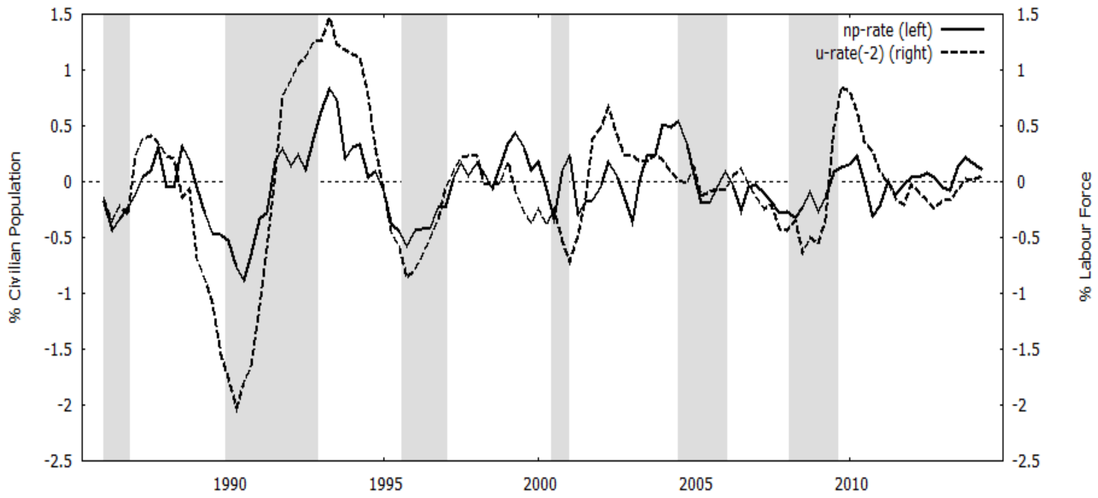
In relation to the Australian data it seems uncontroversial to assert that the participation rate is procyclical during our sample period as we now illustrate. We compare the non-participation rate (which we define as 100% minus the participation rate) with the unemployment rate which it is reasonable to assert is countercyclical. If participation is procyclical then non-participation must be countercyclical, so we expect positive co-movement between non-participation and unemployment[4]. We extract the cyclical component of each using a Hodrick-Prescott filter with a smoothing parameter of 1600 and we lag unemployment by two periods to aid illustration as presented in Figure 2. In the figure we see that there is apparent positive co-movement between the cyclical components of the non-participation rate and unemployment rate, particularly in the early part of the sample period which encompassed the 1991 recession. Non-participation and unemployment tend to rise during the contraction phase of a major

[3] DWE also incorporates previously discouraged workers who become 'encouraged' when the business cycle turns upwards.

[4] We could have compared the participation rate directly with a business cycle indicator like GDP but, due to the high levels of persistence in both participation and unemployment, the relationship was most evident between our chosen variables.

economic cycle and to decline in the growth phase. We view this graphical result as prima facie evidence that participation is procyclical. This observation is consistent with the DWE dominating the AWE in our sample. Later in section 3.6 we conduct a more formal analysis of business cycle characteristics of several variables using a cross-correlogram.

Figure 2. Cyclical components of the non-participation rate and unemployment rate



Notes. Cyclical components of each series were generated using a Hodrick-Prescott filter with smoothing parameter 1600. The unemployment rate is lagged by two periods. Shaded periods in this report indicate a contraction phase of the Growth Cycle as determined by the Melb. Instit. (Melbourne Institute, n.d.).

3. Description of the data

3.1. Labour market stock variables

The period of study in this report is January 1986 to June 2014. The Australian Bureau of Statistics ('ABS') provides monthly series of the number of employed and unemployed persons along with the participation rate and the size of the Civilian Population[5] in ABS Catalogue 6202. These series have been obtained in original as well as seasonally adjusted terms. We can determine from these series the number of civilians not participating in the labour force (referred to variously in the literature as 'Non-

[5] Civilians aged 15 years and over.

participation', 'Not in the Labour Force' or 'Inactive'). Any of the original or derived stock variables may be expressed as a percentage of the Civilian Population[6].

In October 2014 the ABS announced that they were suspending publication of certain seasonally adjusted labour force series pursuant to a review of the methodology of seasonal adjustment. Series from July 2014 were deemed to have been affected. A sample period ending in June 2014 will be used for this report to avoid using data which may be subject to revision whilst the ABS seeks to re-establish valid patterns of seasonality.

3.2. Gross flows in the labour market

Quarterly gross flows of people between three labour market states of Employment, Unemployment and Non-participation have been generated from gross changes in stocks derived from matched records in the labour force survey and published in ABS catalogue 6202, data cube GM1, for the period August 1991 to December 2014. Electronic records of ABS catalogue 6203 were used to source gross flow data from January 1986 to July 1991 as originally published without adjustment. ABS catalogue 6203 does not provide data for the four monthly periods ending September 1987 to December 1987 inclusive since, during that time, the ABS was implementing a transition to a new sample in the underlying survey. Linear interpolation between the corresponding months in the prior and following years was used to generate the missing data points[7].

Transitions between labour market states are determined by matching respondents in consecutive monthly editions of the survey and noting their opening and closing status. For example a person can be measured as having moved from Employment to Unemployment during the month. Due to ongoing rotation of the sample and a varying degree of non-responses each month ABS estimates that the matched records reflect only about 80% of the sample and that the final published raw data will reflect only about 80% of the population values[8].

[6] See Appendix 4 for a table of data sources and definitions of variables used in this report.
[7] These estimates will affect 2 of 114 quarterly observations in relevant regression analysis that follows in this report.
[8] See ABS 6102.0.55.001 - Labour Statistics: Concepts, Sources and Methods, 2013, Chapter 20 Labour Force Survey.

3.2.1. Transformation of gross flows

A number of transformations have been performed on the gross flow data to make it consistent with the stock data. If there were an exact correspondence between stocks and flows then first differences of a time series of stock data would equal the net difference between inflows and outflows calculated from flow data. We follow a procedure described in detail by Dixon, Freebairn and Lim (2004) first to 'gross up' the raw data from representing approximately 80% of the population to 100% of the population[9] and secondly to modify individual flows to make the flow series as close as possible to being consistent with the changes in the stock data series. In brief, the procedure may be described as follows. It is useful to refer to an example set of raw observations of gross flows for one particular month, as illustrated in Table 1.

Table 1. Labour Force status: Gross Flows March 2014

Persons ('000)	*LF Status March 2014*			
LF Status February 2014	*Employed*	*Unemployed*	*Not in the Labour Force*	February Row Totals
Employed	8,890.7	75.7	234.6	9,201.0
Unemployed	155.8	344.0	151.1	650.9
Not in the Labour Force	200.8	152.8	4,590.9	4,944.5
March Column Totals	9,247.3	572.5	4,976.6	14,796.4

In the example shown in the table, 75.7 thousand people transitioned from employment to unemployment between the February and March surveys. Row totals should correspond with the stock totals in February and the column totals should correspond with stock totals in March. Raw gross flows are not seasonally adjusted so there should be logical consistency between gross flows and original (not seasonally adjusted) stock data. An iterative procedure is used whereby all of the numbers in each row of the matrix are multiplied by a ratio calculated to make the new row total consistent with the actual

[9] The process of grossing up the size of the sample from 80% to 100% is only valid if the missing respondents had the same distribution of transition characteristics as the remaining 80% from which they are estimated. The ABS estimates that only about two thirds of the unmatched 20% portion is likely to have similar characteristics to the matched group.

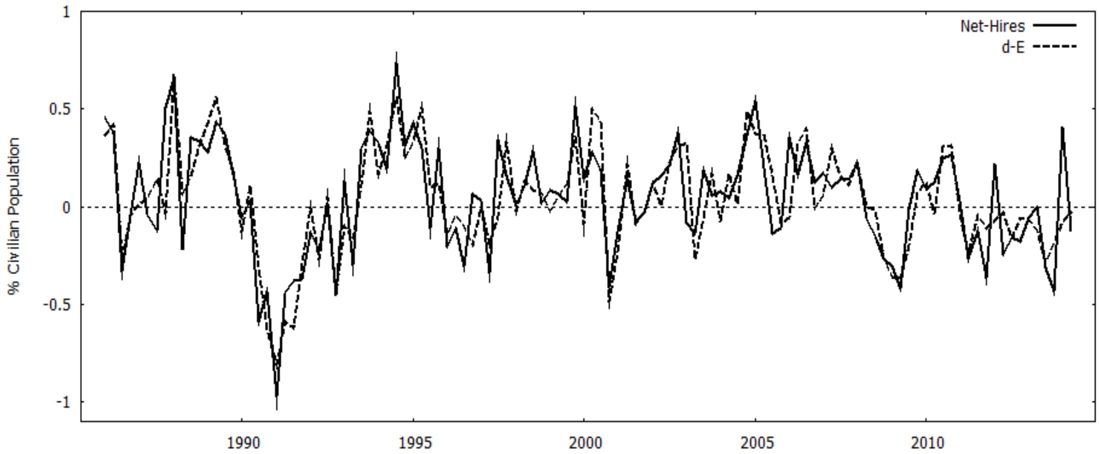
stock data for the opening month. Such adjustment will not automatically generate consistent column totals so the corresponding process is applied each column of the matrix to make the column totals consistent with the actual stock data of the closing month. Adjusting the columns will upset the adjustment of the rows and vice versa. We repeat the pair of adjustments by row and by column until there is no significant change to the transformed flows after successive pairs of adjustments. The process does not generate a solution in which both row and column totals match actual stock totals *exactly* due to anomalies in the actual data. The average discrepancy between column totals and stock totals after the final iteration for our sample data was 0.13%[10].

The transformed series of monthly gross flows were then seasonally adjusted using X-12-ARIMA. The monthly series are still quite noisy. Later we will compare the labour market data with a proxy variable for the output gap which is only available at a quarterly frequency, so it is convenient to simply aggregate the monthly seasonally adjusted gross flow series into an equivalent quarterly series.

Figure 3 provides an illustration of the level of remaining discrepancy between quarterly changes in the Employment pool derived from (a) first differences in the stock variable and (b) the combination of the gross flows corresponding to the net inflow to Employment (net-Hires). The measure derived from flows appears to be noisier than the series derived from the stock variables, as we would expect, but otherwise appears to capture the characteristics of changing employment levels satisfactorily.

[10] Iterations of pairs of row and column adjustments were continued until the improvement between successive pairs of iterations was less than 0.001% of the target stock total. Typically this took 30-50 iterations.

Figure 3. First differences in Employment stock vs. net-Hires (flows)

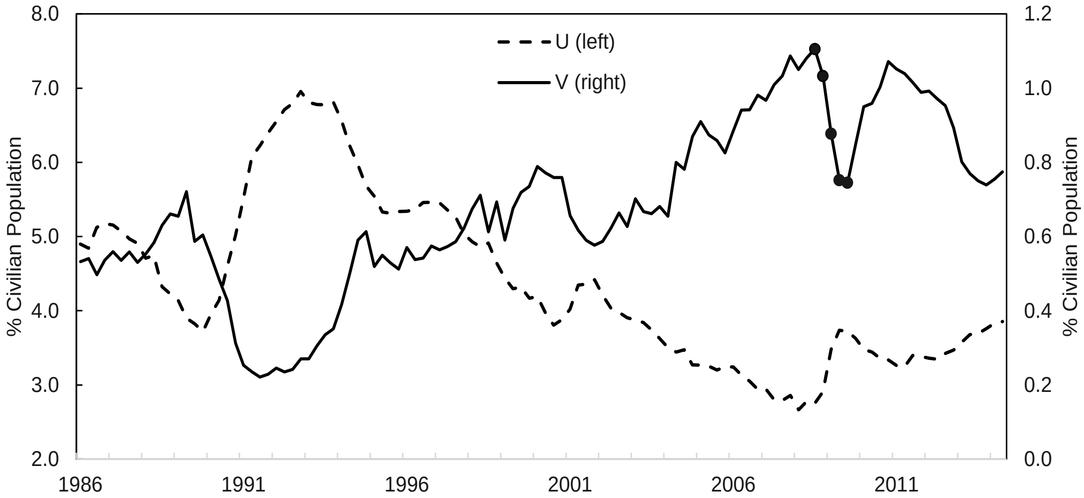


3.3. Job vacancies

The ABS produces a quarterly time series of Job Vacancies for Australian States and Territories which are available in Catalogue 6354 from which we have extracted the Job Vacancies Australia (total) series. The series only includes vacancies which are available to be filled immediately and for which the employer is actively recruiting. Certain vacancies are excluded such as those available only to internal candidates or for work to be carried out by contractors[11]. The ABS Job Vacancies series contains a gap from August 2008 to August 2009 during which time the survey was not conducted. The survey was re-established in November 2009 but the ABS was not able to fill the gaps retrospectively. We have used a quintic spline to generate the missing points. Clearly this is far from being ideal but it was desirable to allow this study to incorporate data which spanned the period of the global financial crisis. Figure 4 illustrates the Job Vacancies series, including the interpolated data, plotted against the unemployment rate for the same period. The performance of the vacancy series during the crisis period looks plausible but, beyond that, there is nothing that can be done to retrieve the true depth and timing of the likely fall in vacancies during this period.

[11] See ABS 6102.0.55.001 - Labour Statistics: Concepts, Sources and Methods, 2013, Chapter 11 Job Vacancies Labour Force Survey.

Figure 4. Unemployment rate and vacancy rate



Notes: U and V are expressed as percent of Civilian Population. Interpolated points for missing observations in the original Job Vacancies series are highlighted.

3.4. Scaling by civilian population

Many labour market studies consider the behaviour of the stock variables relative to the size of the labour force (employment plus unemployment) and in some cases the size of the labour force is assumed to be constant. In this study it is of interest to allow the size of the labour force to vary endogenously relative to the size of the Civilian Population. We do not seek to explain the behaviour of the size of the Civilian Population through time. Accordingly we will rescale all of the stock variables and gross flows and express them as a percentage of the Civilian Population. By construction we can then make use of the identity

$$E+U+N=100$$

where E, U and N are, respectively, the number of people in Employment, Unemployment and Non-participation divided by Civilian Population and multiplied by 100. We can think of each of E, U and N as being rates. It is important to note that this definition of U is different to the conventional definition of the unemployment rate which uses the size of the labour force as the denominator. However if required we may easily derive results in terms of the conventional unemployment rate using the simple relationship $u\_rate = 100 \times U/(U+E)$. Gross flows will also be scaled by Civilian

Population and the variables representing the flows will be in lower case letters as defined in Table 2.

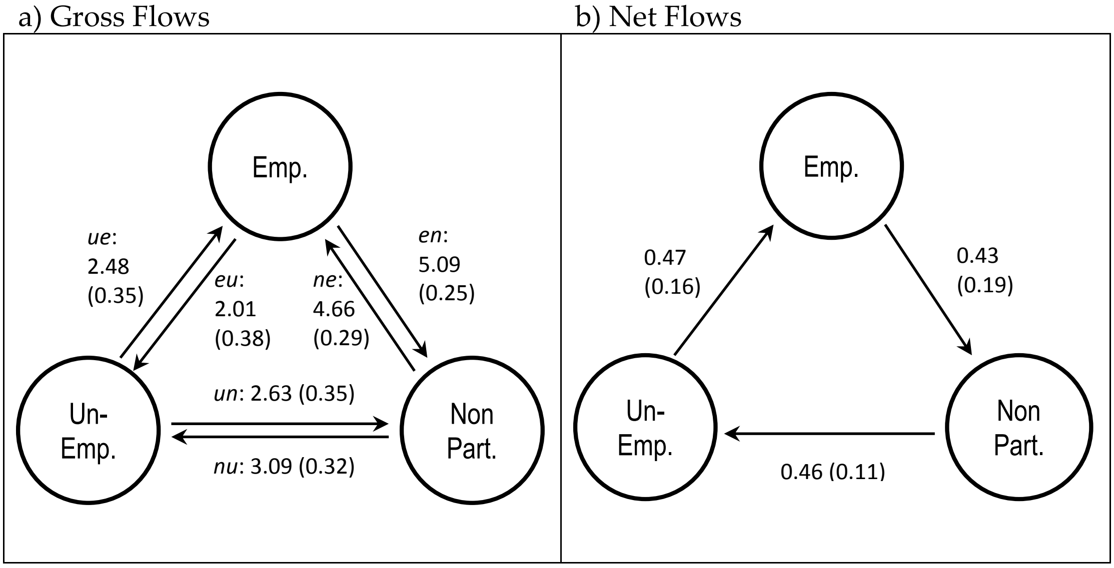
Table 2. Quarterly gross flow variables

Gross Flow Variable	Origin	Destination
eu	Employment	Unemployment
ue	Unemployment	Employment
en	Employment	Non-participation
ne	Non-participation	Employment
un	Unemployment	Non-participation
nu	Non-participation	Unemployment

3.5. Preliminary analysis of the gross flows

Figure 5 shows a diagrammatic representation of the average gross and net flows between each of the three labour market states during the sample period. We observe that the largest average gross flows are between the states of Employment and Non-participation. This may be counter to an intuition that flows between Employment and Unemployment would be the largest and most volatile of the flows. This highlights the potential advantage of a three state model which can incorporate an endogenous participation rate. We also observe that the magnitude of gross flows is large in comparison to absolute net flows to or from any particular stock. For example, we define 'Hires' as total gross flows into Employment (ue and ne) and 'Separations' as total flows out of Employment (eu and en). Figure 6 compares Hires and Separations with net Hires. There is evidently a strong relationship between Hires and Separations generally with only small net flows into or out of Employment each quarter. Average gross Hires and Separations are 7.14% and 7.10% respectively, generating net Hires of only 0.04%.

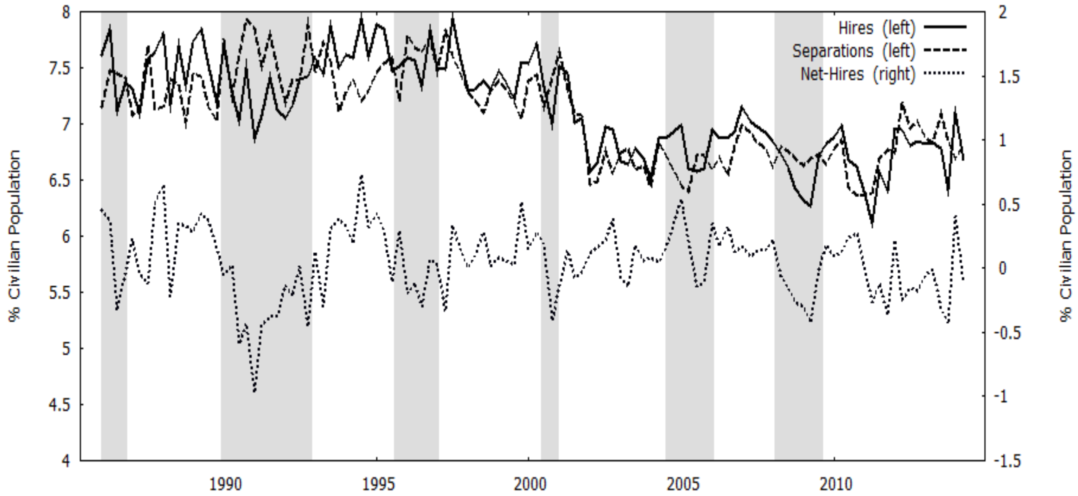
Figure 5. Summary of quarterly flows: sample period 1986:Q1-2014:Q2



Notes: Average quarterly flow as a percentage of Civilian Population. Standard deviation shown in parentheses.

We can also consider net flows between any pair of nodes as shown in panel (b) of Figure 5. The average net flows have moved in a clockwise direction given the chosen order of nodes. Average inflows to any particular node have approximately offset average outflows so that we have observed only small average net changes in each of the stock variables. Unemployment and Non-participation fell on average over the study period whilst Employment rose. It is tempting to interpret the net clockwise flow as capturing a demographic life-cycle (Dixon, Lim, & van Ours, 2015, p. 3), i.e. a cycle in which school leavers and other first time graduates join the workforce primarily through the unemployment pool before eventually progressing to employment and notionally replacing older workers who are moving from employment into non-participation, such as by retirement. As tempting as that characterisation may be we cannot exclude the possibility that our observation is entirely sample specific and that a different pattern may emerge in another age with a different demographic trend.

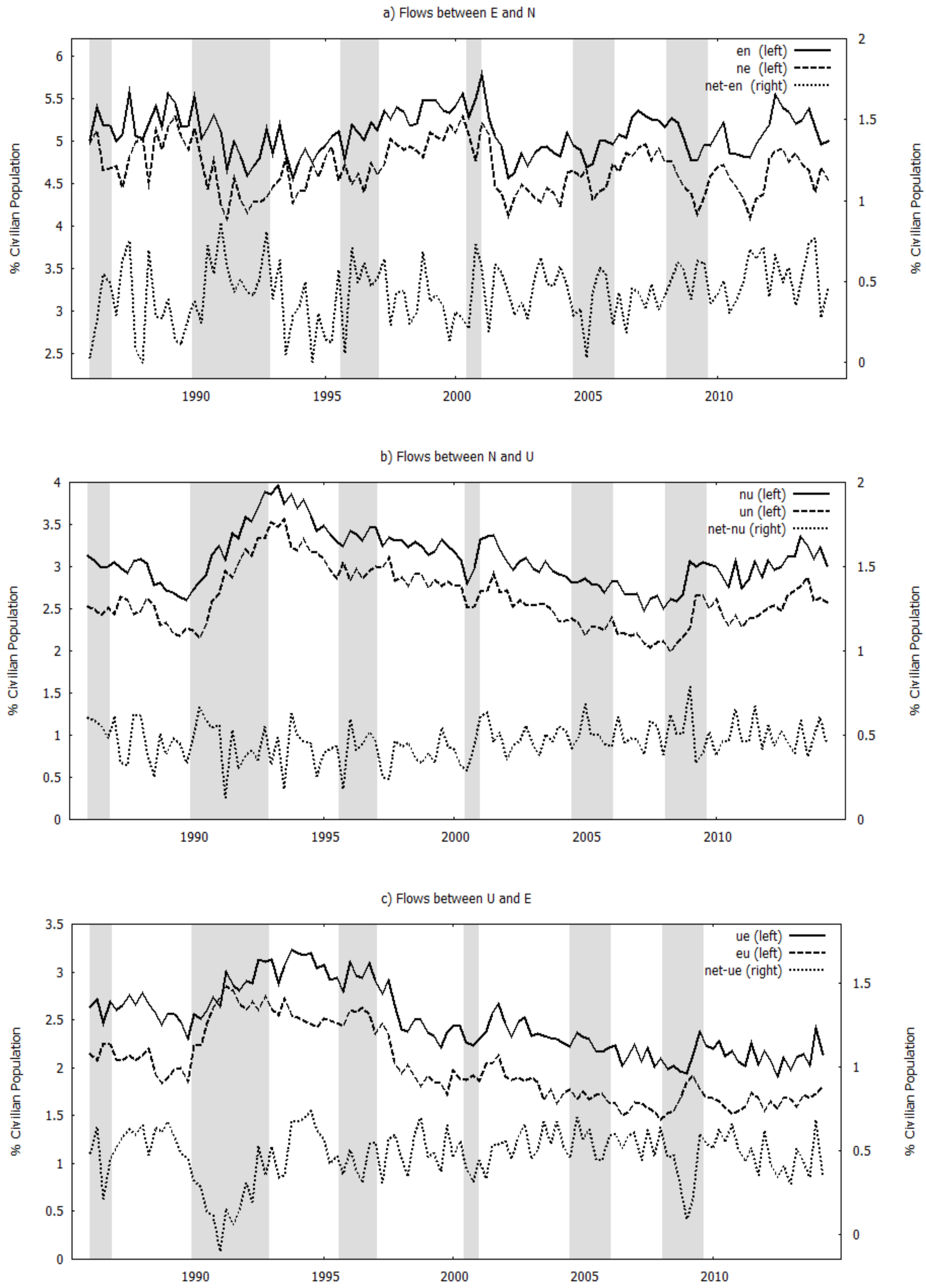
Figure 6. Hires and Separations from Employment



Notes: Shaded periods indicate a contraction phase of the Growth Cycle.

There also appears to be a strong relationship between each pair of gross flows between any pair of nodes as illustrated in Figure 7. It is interesting to observe that the gross flows in each pair tend to move in the same direction as one another during each phase of a business cycle. For example, in Figure 7(c) we observe that during the most recent economic downturn *both* flows eu and ue increased, perhaps counter to an intuition that flows from unemployment to employment would fall during a downturn. Whilst eu and ue appear to move parallel to one another most of the time, we can observe a distinct narrowing of the spread between them near the start of the major economic contractions, which would have contributed to a net increase in U relative to E in the absence of any change in flows to or from N. The narrowing of the spread between eu and ue could reflect a slight phase difference (where for example eu increases earlier than ue) or a persistent change in the difference between them. We note that only small changes in the relative magnitude of a pair of gross flows, or a small change in the phase difference between them, can be sufficient to generate a material change in a stock variable due to the large size of gross flows relative to net flows.

Figure 7. Quarterly gross and net flows as a percentage of Civilian Population



Notes: Quarterly time series of the aggregate seasonally adjusted flows, 1986Q1-2014Q2. Shaded periods indicate a contraction phase of the Growth Cycle as determined by the Melbourne Institute.

To summarise key observations based on visual inspection of Figure 7, we find that eu, ue, nu and un are probably countercyclical and that en and ne are procyclical. We will examine the business cycle characteristics of the stocks and flows more closely in later analysis.

3.6. Business cycle characteristics of stocks and flows

We aim to build a model to help explain fluctuations in labour market variables at a business cycle frequency. First we illustrate some stylised business cycle characteristics of the sample data. We use a measure of the output gap as a business cycle indicator. A Hodrick-Prescott filter was applied to the log of real Australian GDP with a smoothing parameter $\lambda = 1600$ which is widely used in the literature for data with quarterly frequency and we define Y to be the cyclical component of the filtered series. Similarly we have extracted the cyclical component of the quarterly time series of each stock variable and gross flow variable so that they may be compared with the business cycle indicator in a cross-correlogram[12].

Table 3 shows the correlation coefficient between series $Y(t)$ and $X(t+i)$. For the central column with $i = 0$ the value is the contemporaneous correlation between Y and X. Positive values of i mean that $X(t+i)$ is observed after $X(t)$. We interpret significantly positive correlations as an indicator that a series is procyclical and significantly negative correlations as an indicator that the series is countercyclical. If the correlation for $X(t+i)$ where $i > 0$ has the same sign as the correlation for $X(t)$ but the former is larger in absolute value then we interpret this as an indicator that series $X(t)$ lags (peaks later than) $Y(t)$. Similarly we can interpret $X(t)$ as leading $Y(t)$ when equivalent conditions prevail for $i < 0$. The value of i for which the correlation coefficients are maximised is an indicator of the number of periods by which $X(t)$ lags (or leads) $Y(t)$.

The results presented in Table 3 shows that employment and unemployment are procyclical and countercyclical respectively, as would be anticipated. Each of them lag

[12] We follow a format used by Fisher, Otto and Voss (1996).

output by about two periods (quarters). Non-participation (N) is countercyclical (significant at 5%) and appears to lag output by as many as four periods. The table also includes the labour force participation rate which is related to N by the identity $PR = 100 - N$. Obviously the cyclical properties of PR will be the mirror image of those of N but it has been included in the table since it is more typical in the literature to discuss the properties of PR than N. Thus we can say that we find empirical evidence significant at 5% that PR is procyclical. The vacancy rate is also strongly procyclical and appears to be concurrent with, or possibly slightly leading, output. The observation that V leads U is consistent with theory which posits that the level of vacancies is set by firms in a forward looking manner with regard to expected levels of output and profitability. Opening a new job vacancy is not subject to the level of inertia that constrains rapid changes in employment and unemployment so V can jump immediately to a new level when business conditions change (Cahuc & Zylberberg, 2004, p. 546).

The cross-correlograms for the gross flows confirm earlier intuition, based on inspection of the charts presented in Figure 7, that the flows en and ne are procyclical whilst eu, ue, nu and un are countercyclical, in each case significant at 1%. The flows en and ne are approximately concurrent with output whilst nu and un appear to lag output by one or two periods. The flow eu appears to lead output by one or two periods whilst ue appears to lag output by up to three periods. The degree by which eu leads output seems a little implausible and is likely to be a statistical anomaly. In results not shown in this paper we conducted the same cyclicality analysis using GNE gap[13] rather than GDP gap as the business cycle indicator and the anomaly disappeared since eu was found to be approximately concurrent with GNE whilst ue lagged by about two periods. Cross-correlogram analysis of GDP vs. GNE indicated approximately concurrent cyclical behaviour between them, and we have no reason in theory to expect one to lead the other.

It seems reasonable to conclude that eu is the first mover of any of the six flows but we consider it unlikely that it leads every other variable by as much as two periods. These

[13] Gross National Expenditure.

results support placing eu first amongst the flow variables in following analysis using a VAR model.

Table 3. Business cycle characteristics of stocks and flows

Series X	Std. Dev.	Cyclic-ality	Cross Correlation of $Y(t)$ with series $X(t+i)$: t-4	t-3	t-2	t-1	t+0	t+1	t+2	t+3	t+4	t+5
Stocks^												
E	0.598	Pro.	-0.01	0.14	0.29	0.44	0.58***	0.68	0.72	0.69	0.62	0.51
U	0.388	Ctr.	-0.16	-0.33	-0.48	-0.61	-0.73***	-0.80	-0.78	-0.68	-0.53	-0.37
N	0.298	Ctr.	0.23	0.14	0.05	-0.09	-0.20**	-0.32	-0.42	-0.50	-0.54	-0.53
PR	0.298	Pro.	-0.23	-0.14	-0.05	0.09	0.20**	0.32	0.42	0.50	0.54	0.53
V	0.085	Pro.	0.37	0.48	0.54	0.57	0.57***	0.54	0.45	0.30	0.11	-0.07
Flows^												
en	0.199	Pro.	0.16	0.17	0.25	0.30	0.36***	0.35	0.35	0.32	0.19	0.17
ne	0.232	Pro.	0.23	0.29	0.34	0.40	0.48***	0.48	0.39	0.35	0.16	0.07
eu	0.140	Ctr.	-0.44	-0.58	-0.65	-0.67	-0.58***	-0.48	-0.34	-0.18	-0.05	0.09
ue	0.130	Ctr.	-0.07	-0.21	-0.23	-0.29	-0.29***	-0.39	-0.48	-0.49	-0.44	-0.27
nu	0.161	Ctr.	-0.06	-0.19	-0.31	-0.43	-0.48***	-0.57	-0.57	-0.52	-0.45	-0.35
un	0.164	Ctr.	0.03	-0.13	-0.29	-0.40	-0.53***	-0.57	-0.61	-0.58	-0.51	-0.38

Notes: Y is the cyclical component of the log of real GDP. ^The cyclical component of each of the stock and flow variables was used to determine the standard deviations and the correlations with Y. Significance levels are shown only for the contemporaneous correlation coefficients (***, ** and * indicate 1%, 5% and 10% respectively). The apparent cyclicality indicated in the third column has been determined solely by reference to the sign of the contemporaneous correlation coefficient.

3.7. Flow-rates

We have defined gross flows as a percentage of Civilian Population and we may think of this measure as being equivalent to a *number* of workers from a fixed population of one hundred. We can also define a flow-rate which expresses the number of workers in the gross flow as a percentage of the number of people in the pool from which the flow originated. For example, we define $\lambda_{eu} = 100 \times eu / E$ to be the (full period) flow-rate from state E to state U as a percentage of E. Under certain conditions the flow-rate is synonymous with the state transition probability of a representative individual in the originating pool.

It can be debated whether a flow-rate so defined can be thought of as a deep underlying parameter of an economic model which drives the number of people who make a specific state transition within a period, or whether the flow-rate is simply a derived quantity which we calculate from the level of gross flows and stock variables. In essence the question is whether the flow-rate *causes* the number of people in the flow, or vice versa. Current theory does not resolve the question, since different models of the labour market may be framed either in terms of the levels of flows or the flow-rates. In the former case, even if there is no change to the process generating the level of flows, a change in stock levels will automatically generate a change in flow-rates, as described by Elsby, Michaels and Solon (2009, pp. 105-106). In the latter case flow-rates may be assumed to be fixed (but subject to exogenous influences) in which case a change in stock levels will automatically generate a change in the level of gross flows. In our analysis we will model changes in the levels of stocks and flows so it will be appropriate to interpret flow-rates as derived quantities.

3.7.1 Full period and instantaneous flow-rates

Labour surveys conducted at discrete intervals, by which the gross flows are determined, will not capture multiple transitions by individuals within one measurement period so full-period transition rates will underestimate the true level of gross flows. Shimer (2012) developed a methodology to deal with this so-called time aggregation bias by calculating instantaneous transition rates which are assumed to be constant within each period[14]. In this paper, however, we will use a SVAR model to generate impulse response paths for stock variables at discrete intervals and corresponding full-period gross flows, and from these derive full-period flow-rates. Accordingly, our flow-rates will not be directly comparable with instantaneous transition rates derived by other authors.

3.7.2 Job-finding and job-separation rates

There has been much debate in the literature about the relative importance of the job-finding and job-separation rates to the variance of the steady state unemployment rate. Hall (2005, p. 398) showed that in a simple two-state model (with only unemployment

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[14] If α is the instantaneous transition rate from a normalised pool then the size of the pool remaining after time t is $e^{-\alpha t}$, and the volume which transitioned out of the pool during the period is $(1-e^{-\alpha t})$.

and employment) there is a simple relationship between the stationary unemployment rate and the rates of job-finding and separation. If the job-finding rate f (the fraction of the unemployed finding a job during a period) and the job-separation rate s (the fraction of employed who leave employment) are constant, then the stationary unemployment rate[15] u is given by:

$$u = \frac{s}{s + f}$$

Hall found that the actual rate of unemployment closely tracked this estimate of the stationary level in the United States. An equivalent relationship for the steady state unemployment rate in a three state model (employed, unemployed and inactive) can be found in Shimer (2012, pp. 135-136). Many authors have used this framework for analysing cyclical changes to the unemployment rate and to measure the contributions of s and f to the historical variability of the unemployment rate. Shimer (2005) finds that the job-finding rate is strongly procyclical whereas the job-separation rate is only weakly countercyclical. Using United States data from 1948-2010, Shimer (2012) finds that the job-finding rate has accounted for about 77% of fluctuations in the unemployment rate since 1948 and for about 90% since 1987. Hall (2006) finds from United States data that the job-finding rate is highly procyclical but that the rate of layoffs and other separations do not rise during a recession. He finds that the job-finding rate is the key to understanding the fluctuations in the unemployment rate, noting that the separation rate has been stable.

Other authors have made findings that conflict with some of the conclusions of Shimer and Hall. Fujita and Ramey (2009) found that the separation rate was highly countercyclical and that it accounted for 40-50% of fluctuations in unemployment. Yashiv (2007) found that both job-finding and job-separation rates are important for understanding the business cycle. Petrongolo and Pissarides (2008) analysed three European labour markets and found a mixture of results with regard to the relative importance of job-finding and job-separation rates. In Australia, Ponomareva and Sheen

[15] Unemployment rate expressed in the conventional form as a percentage of the Labour Force.

(2010) found that both job-finding and job-losing were important. For their whole sample period (1980:8-2009:6) they found that job-losing was more important than job-finding but that since 1993 job-finding had become more important, particularly during recessions.

Later, we will be able to make some observations about the contributions of different flows to the unemployment rate using our model. These will not be directly comparable with the work of the authors referenced above since our model will apply shocks to flows, rather than flow-rates, but will address a comparable question of the relative importance of inflows and outflows to the variability of unemployment.

3.8. Added-Worker Effect and Discouraged-Worker Effect

The micro-foundations of the AWE and DWE are expressed in terms of behavioural responses of individual people and discrete households. If we mean to classify particular changes in the aggregate labour market variables as being consistent with either AWE or DWE it is therefore necessary to look at flow-rates rather than gross flows. The change in a flow-rate can be interpreted as the change in the probability of a representative person making a particular transition, or the change in the proportion of a pool of fixed size who make a transition. Changes in gross flows, on the other hand, potentially capture both a change in transition probability and a change in the size of the pool. For example, the seemingly anomalous rise of the gross flow ue in a recession may be explained by an *increase* in the size of the unemployment pool which more than offsets the fall in the job-finding probability.

We will have a particular interest in the four flow-rates that affect the participation rate directly[16]; i.e. all the flows to or from N. To facilitate commentary on following analysis of impulse responses we make the particular definitions of AWE and DWE given in Table 4 which apply to all following sections of this paper. Defined responses are only stated in the table for negative shocks to the business cycle since AWE and DWE are

[16] In the context of a multi-period analysis we could claim that all six flows can affect N, since even a flow between E and U in the current period may have an effect on flows to or from N in *subsequent* periods. For simplicity we restrict consideration to flows which affect N in the current period.

typically described in a recession scenario. Responses to positive shocks would have opposite sign[17].

Table 4. Definitions of AWE and DWE in terms of aggregate flow-rates

Defined Term	Description of the dominant behaviour	Response of specific aggregate flow-rates to a negative business cycle shock	Cyclicality of λ
Added-Worker Effect (AWE)	An increase in the probability of workers joining, or staying in, the labour force ('LF') in an economic contraction.	increase in $\lambda_{nu}, \lambda_{ne}$ (joining LF)	Counter-cyclical.
		decrease in $\lambda_{un}, \lambda_{en}$ (leaving LF)	Procyclical
Discouraged-Worker Effect (DWE)	A decrease in the probability of workers joining, or staying in, the labour force ('LF') in an economic contraction.	decrease in $\lambda_{nu}, \lambda_{ne}$ (joining LF)	Procyclical
		increase in $\lambda_{un}, \lambda_{en}$ (leaving LF)	Counter-cyclical

3.9. Interpretation of variation in flow-rates

In Table 5 we show the result of cross-correlogram analysis of flow-rates against the business cycle indicator. We highlight both the gross flow and the originating stock pool from which the flow-rate has been derived, and the empirically determined cyclicality of each of them. The empirical flow-rates have been derived as the quotient of the relevant gross flow and originating stock pool. In some cases the cyclicality of the flow-rate can be readily anticipated. For example, we expect that the flow-rate λ_{eu} will be countercyclical since it is determined as the quotient of eu and E and we have already determined that eu is countercyclical and that E is procyclical. Based on the significance of the contemporaneous correlation coefficient shown in Table 5 we can say that we have evidence, significant at 1%, that λ_{eu} is countercyclical. On the other hand we cannot easily predict the cyclicality of λ_{ue} since both the numerator and denominator are countercyclical. In this case the empirical finding is that λ_{ue} is procyclical, significant

[17] We avoid switching to new terminology for responses under positive shocks to the business cycle as may occur sometimes in the literature, such as 'Subtracted-Worker Effect' and 'Encouraged-Worker Effect'. These represent the *same* psychological behaviour as AWE and DWE respectively; simply operating in the alternate phase of the business cycle.

at 1%. These results are consistent with findings in the literature. Ponomareva and Sheen (2010, pp. 41-42) derive full period transition rates from instantaneous rates in Australia and measure cyclicality with respect to the employment to population ratio as the business cycle indicator. They find that the transition probabilities for job-finding are procyclical whilst for job-separations to unemployment they are weakly countercyclical, more so for women in the period after 1993 and for men during recessions. Elsby, Michaels and Ratner (2015, p. 601) find evidence for a strongly procyclical job-finding rate and marked counter-cyclicality in the job-loss rate in the United States.

Table 5. Business cycle characteristics of full-period flow-rates

		Cyclicality			Cross Correlation of $Y(t)$ with Series $X(t+i)$					
Series X	Std. Dev.	λ	Gross flow^	Origin stock^	t-2	t-1	t+0	t+1	t+2	t+3
Flow-rate										
λ_{en}	0.32	P	*en* (P)	*E* (P)	0.18	0.19	0.22**	0.17	0.17	0.14
λ_{ne}	0.64	P	*ne* (P)	*N* (C)	0.32	0.41	0.50***	0.52	0.45	0.42
λ_{eu}	0.25	C	*eu* (C)	*E* (P)	-0.66	-0.70	-0.64***	-0.56	-0.44	-0.28
λ_{ue}	4.05	P	*ue* (C)	*U* (C)	0.40	0.49	0.63***	0.60	0.48	0.34
λ_{nu}	0.41	C	*nu* (C)	*N* (C)	-0.35	-0.45	-0.48***	-0.56	-0.54	-0.46
λ_{un}	2.85	P	*un* (C)	*U* (C)	0.40	0.47	0.51***	0.55	0.46	0.33

Notes: 'P' and 'C' indicate procyclical and countercyclical respectively. $Y(t)$ is the cyclical component of the log of real GDP. Series $X(t)$ are the cyclical component of each specified λ series. Significance levels are shown only for the contemporaneous correlation coefficients (***, ** and * indicate 1%, 5% and 10%). The cyclicality of each λ indicated in the third column has been determined solely by reference to the sign of the contemporaneous correl. coefficient. ^The cyclicality of the gross flow and origin stock variables are as reported in Table 3.

It is worth reflecting further on the behaviour of λ_{ue}, sometimes referred to as the job-finding rate, since it can be used to explain the potential ambiguity in some discussions of the gross flows or a level of surprise at their behaviour. A layperson would probably anticipate an increase in flows from unemployment to employment during an economic expansion so it may be surprising at first to find that this flow actually falls (ue is countercyclical). It is only by looking at the job-finding rate λ_{ue} that we can observe the more intuitive result that a representative person who starts a period in the unemployed state has an increased probability of finding employment during an economic expansion. In similar terms we may describe the transition rate λ_{eu} as the job-separation rate and consider whether our empirical observation of a countercyclical separation rate accords with our intuition. Interpretation is clouded by the aggregate nature of our data in which we cannot differentiate between voluntary 'quits' initiated by workers and 'fires' or 'layoffs' initiated by employers. Barnichon and Figura (2012, p. 5) find empirical support in United States data that quit rates are procyclical (as we would expect, workers to cling more tightly to current jobs in a recession) and that layoffs are countercyclical (as we would expect, firms are more likely to layoff a larger portion of their workers in a recession). In relation to our Australian data the separation rate must reflect a net effect of quits and layoffs and we conjecture that the net observed counter-cyclicality of the separation rate shows that the business cycle behaviour of fires and layoffs has dominated that of voluntary quits in our sample.

We take the empirical findings of the cyclicality of the flow-rates involving N from Table 5 and characterize them as being consistent with either AWE or DWE and we summarise the findings in Table 6. We could have readily anticipated that λ_{ne} would be procyclical since ne is procyclical and N is countercyclical. By referring to our definitions in Table 4 we claim that this consistent with DWE. We found that λ_{en} is procyclical with the contemporaneous correlation coefficient being positive with 5% significance, which is consistent with AWE. We found that λ_{nu} is countercyclical, significant at 1%, which is consistent with AWE. We found that λ_{un} is procyclical, significant at 1%, which is consistent with AWE.

To illustrate some of these findings more clearly consider the flow-rates between N and U in both directions. Countercyclical λ_{nu} is evidence that people who are currently non-participants have a higher probability (on average) of moving into unemployment (and therefore participating in the labour force) during an economic contraction, consistent with AWE. Similarly, procyclical λ_{un} is evidence that people who are currently unemployed have a lower probability (on average) of moving out of the labour force into non-participation during an economic contraction. This behavior may arise (for example) because the unemployed person becomes more concerned that other members of their household may lose employment due to the contraction, so the unemployed person has increased incentive to continue searching for work, and perhaps to retain access to an unemployment benefit. This behaviour is consistent with AWE.

Table 6. Business cycle characteristics of participation decisions

Rate	Characteristic Cyclicality	Dominant Theoretical Effect (AWE/DWE)
Flow-rates		
λ_{en}	Pro.	AWE
λ_{ne}	Pro.	DWE
λ_{nu}	Ctr.	AWE
λ_{un}	Pro.	AWE
Total Participation Rate		
PR	Pro.	DWE

Notes: The characteristic cyclicality of the flow-rates are as reported in Table 5. The cyclicality of PR is as reported in Table 3.

It is intriguing that AWE dominates DWE on three of the four transitions shown in Table 6, yet the behavior of the overall participation rate is dominated by DWE. It is entirely plausible that the gross flow ne dominates the overall cyclicality of the participation rate since we can observe in Figure 5 that ne is the second largest gross flow on average, and in Table 3 we can see that the cyclical component of ne is also the most volatile of any of the flows.

These results are generally consistent with findings in the literature. Ponomareva and Sheen (2010) calculate full period transition probabilities from instantaneous transition probabilities and derive results separately by gender and by full-time or part-time employment status, so their results are not directly comparable with ours. However, if we take their results for flows corresponding most closely with ours and use our notation, Ponomareva and Sheen (2010, pp. 41-44) find that λ_{ne} is procyclical for part-time employment and that λ_{un} is weakly procyclical. They find that λ_{nu} is weakly countercyclical, significantly so only since 1993. Similarly Elsby et al. (2015, pp. 601-604) find that in the United States λ_{ne} and λ_{un} are procyclical and that λ_{nu} is countercyclical.

They do not discuss the cyclicality of λ_{en} directly but interpretation of their graphical presentation of λ_{en} suggests that it tends to decline in recessions and that it is weakly procyclical.

Our preliminary analysis has shown that it is possible, using only aggregate data, to identify whether the dominant behavior is consistent with AWE or DWE in each of the four types of flow that directly affect participation. There are limits, however, to the level of quantitative understanding of labour market dynamics that can be attained using cross-correlograms as the primary diagnostic tool when there are several interacting variables. In section 5 we will use a SVAR model to make a more rigorous assessment of the dynamic responses of key variables to orthogonalised shocks, including shocks to a business cycle indicator.

4. Relationship between unemployment and vacancies

4.1. Search and matching theory

We will use a SVAR model to examine the business cycle dynamics of a set of labour market variables. Prior to specifying the model we consider whether there is a long term relationship between U and V which needs to be accommodated. Search and matching model theory posits that there is a pool of job searchers and a pool of job vacancies and an inefficient process by which they are matched to create new hires. Presumed asymmetry of information and various forms of mismatch in terms of skill or geographical location can provide plausible micro-foundations for the slow propagation of shocks (for a detailed discussion of micro-foundations of search and matching theory see Cahuc and Zylberberg (2004), Blanchard and Diamond (1989) and Pissarides (1986)).

4.2. Aggregate matching function and the Beveridge Curve

At an aggregate level search and matching theory is typically applied by assuming the existence of an aggregate matching function which describes the number of matches ('hires') that will be made in a period from a pool of workers searching for a job and a pool of vacancies which employers are seeking to fill. The matching function is often assumed to have a Cobb Douglas form, reminiscent of a production function, with arguments of the prevailing level of unemployment and of vacancies:

$$H = h(U,V) = AU^{\alpha}V^{1-\alpha}$$

Blanchard and Diamond (1989, p. 29) found empirical support for a model in this form with constant returns to scale and this has been a typical assumption in much of the following literature (Petrongolo & Pissarides, 2001, p. 397). A possible definition of equilibrium is one where the number of hires is equal to the number of separations from employment. If we only consider flows between employment and unemployment and further assume that the number of separations from employment is proportional to the size of the pool of employed (constant separation rate 's') then we can write the equilibrium condition as:

$$sE = AU^{\alpha}V^{1-\alpha} \tag{2}$$

For ease of illustration let us normalise A to one. Since we have assumed that $h(U,V)$ is homogeneous of degree one we can divide through both sides of (2) by E to derive the relation:

$$s = u^{\alpha}v^{1-\alpha} \tag{3}$$

where $u = U / E$ is a measure of the unemployment rate[18], $v = V / E$ is the vacancy rate and s is assumed to be constant. Then equation (3) provides a theoretical foundation for a rectangular hyperbola shape of the relation between u and v, the so-called Beveridge Curve.

4.3. Returns to scale

Now we test the empirical validity of the theory with our sample data. First we test the validity of the typical assumption that there exists an aggregate matching function with constant returns to scale. We use the following general form[19] to describe the matching function:

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[18] The conventional measure uses the size of the Labour Force as the denominator.
[19] Similar to the form used by Groenewold (2003).

$$H = A\left(\prod_{i=1}^{k} Z_i^{\gamma_i}\right)U^{\alpha}V^{\beta} \tag{4}$$

H represents total hires (matches) made in a calendar quarter measured as a percentage of the civilian population. U and V are also measured as a percentage of the civilian population. Constant returns to scale with respect to the unemployment and vacancy inputs requires $\alpha + \beta = 1$. There are k $(k \geq 0)$ so-called shift variables Z_i which reflect a change in search intensity or matching efficiency for a given level of U and V. We take logs of both sides of (4) so that we can estimate the elasticities. Illustrated for the case where there is only one shift variable Z we estimate an equation of the form:

$$\ln H_t = \ln A + \gamma \ln Z_t + \alpha \ln U_t + \beta \ln V_t + \varepsilon_t \tag{5}$$

Hires can be taken to mean only flows from unemployment to employment or it can also include flows from non-participation to employment, as we do. For this latter flow to be relevant to the theory we have to assume that the size of the unemployment pool is a reasonable proxy for the number of people searching for jobs. It is well known that the Non-participating pool will include a number of people who want work but who do not satisfy the criteria for active search to be counted as unemployed. Such workers are typically described as 'marginally attached' (Jones & Riddell, 1999, p. 149). If the size of the pool of marginally attached workers is small compared to total Non-participation and if it moves approximately in proportion with the unemployment pool then unemployment may be a reasonable proxy for the total number of people searching for work, with varying degrees of intensity. This is not entirely satisfactory but at the same time it is difficult to exclude the flows from non-participation to employment since they are approximately twice as large as the flow from unemployment on average. Finally we note that our data does not allow us to identify flows from employment to employment (direct movements from one job to another). Blanchard and Diamond (1989, p. 15) estimated that 15% of hires in the United States were from workers already in employment.

In Table 7 we present the results of estimating some equations in the form of equation (5) to assess the empirical validity of the assumption of constant returns to scale[20]. It has been observed previously (Blanchard & Diamond, 1989, p. 25; Petrongolo & Pissarides, 2001, pp. 420-422) that a literal interpretation of equation (5) is difficult since the left hand side variable is a flow and the right hand side variables include stocks and, in theory, the former depletes the latter directly during a period. Further, we note that our flows into employment are larger than our proxy for the stock of vacancies. Secondly, our flows are a discrete estimate of an aggregate flow during a defined time period whilst the stock variables are measured at a point in time. This so-called time aggregation bias leads to biased estimates of the elasticities when contemporaneous measures of stocks are used in the regression (Blanchard & Diamond, 1989, p. 28). For this preliminary analysis we simply trial some different specifications, firstly using contemporaneous values of U and V on the right hand side and then an alternative specification where U and V are replaced by their one-period lagged values, which can be interpreted as the opening period stock value.

We also control for potential shift variables which could influence the level of search intensity by workers or firms. Shift variable candidates[21] include the Long term unemployment ratio ('$LTUR$') which is the portion of unemployed who have been unemployed for 52 weeks or more[22]. It has often been conjectured that long term unemployed search with less intensity than other unemployed due to a combination of loss of motivation and a decline in their skill set that makes them less effective searchers (Fahrer & Pease, 1993; Mumford & Smith, 1999; Petrongolo & Pissarides, 2001, p. 411; Webster, 1999). Whilst the micro-foundations of this idea are sound, we do not find $LTUR$ to be a convincing shift variable given our sample data because it is highly correlated with the lagged level of unemployment (see Figure 8). We are contemplating a VAR model which will include lagged terms in U so it is not clear that $LTUR$ will bring much additional information into the model beyond the lagged level of

[20] Stationarity of variables is discussed in section 5.1. Here we proceed under the assumption that the variables are trend stationary and estimate the equations with a time trend.
[21] See Appendix 4 for definitions of these variables.
[22] As defined by ABS for the Australian data series.

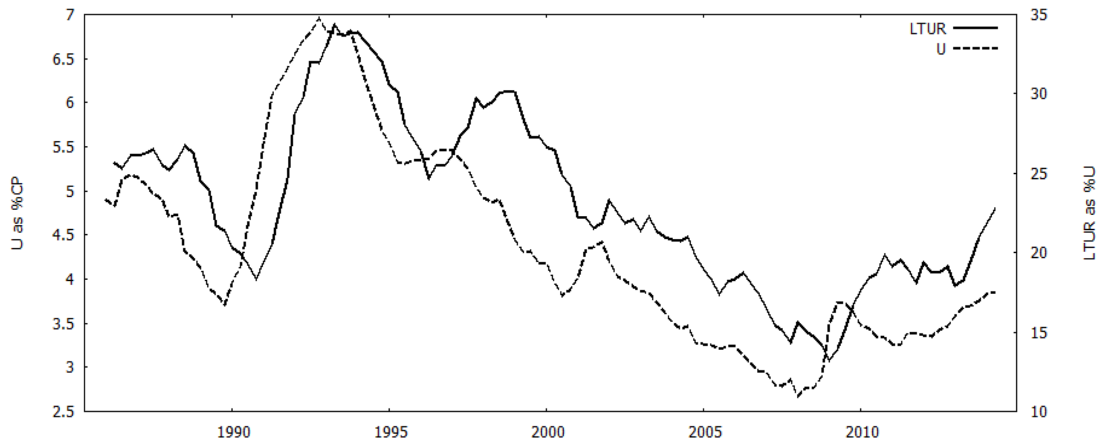
unemployment. The so-called Replacement Ratio ('RR') is the ratio of real wages to the real level of the unemployment benefit and it has been used as a potential shift variable in several Australian studies including Fahrer and Pease (2004) and Groenewold (2003). In theory lower RR would reduce the return to investment in job search and so reduce search intensity for job searchers (Cahuc & Zylberberg, 2004, p. 526). The ratio of full-time employed to total employed ('FTE') may capture a shift towards more casual or more flexible working arrangements and indirectly affect search intensity by firms and workers. This could reflect a combination of change in the composition of the workforce driven by demographic factors and institutional change whereby firms have been moving away from traditional employment arrangements to try and optimise their labour input.

Table 7. Aggregate matching function estimations

	Dependent Variable: log(Hires)									
Specif-ication	Const.	Time	U	V	$LTUR$	RR	FTE	Returns to scale	R^2	LM(4) p-val
1	1.846	-0.001	0.188	0.102				0.290	0.65	0.000
	(0.000)	(0.000)	(0.000)	(0.000)						
2	1.727	0.00050	0.062	0.067	0.112	-0.409	0.709	0.129	0.68	0.007
	(0.000)	(0.644)	(0.266)	(0.004)	(0.005)	(0.171)	(0.188)			
3	1.810	-0.001	0.205	0.100				0.305	0.67	0.000
	(0.000)	(0.000)	(0.000)	(0.000)						
4	1.714	0.001	0.097	0.078	0.098	-0.385	0.656	0.175	0.69	0.007
	(0.000)	0.686	0.078	(0.000)	0.023	0.195	0.220			

Notes: Independent variables except time entered as natural logs. Current values of U and V are used in specifications (1) and (2). One-period lagged values of U and V are used in specifications (3) and (4). Reported results are the OLS regression coefficient and the p-value in parentheses, determined using HAC robust standard errors. BG test statistic for auto-correlation of residuals up to order 4 is shown in the last column.

Figure 8. Long term unemployment ratio vs. Unemployment



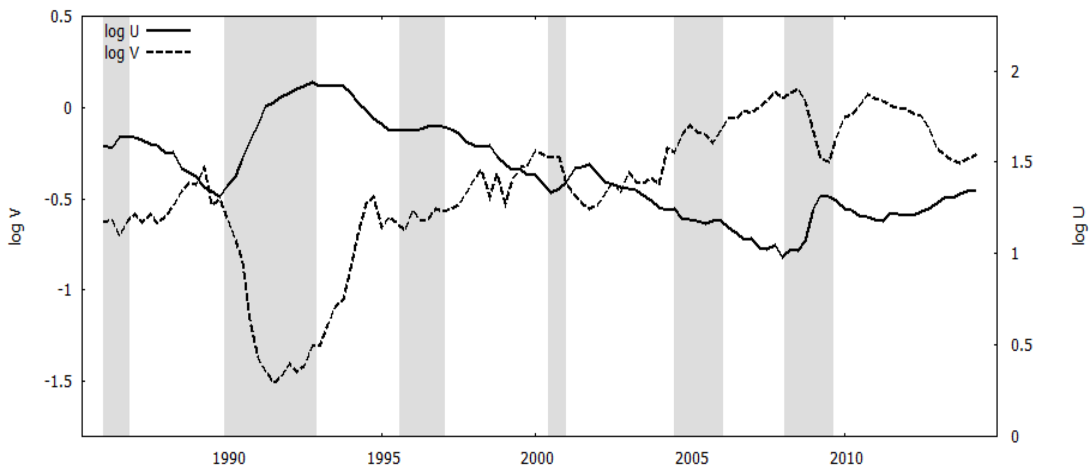
The results in Table 7 indicate a return to scale of around 0.30 with either specification of current or lagged stock values, and even lower return to scale when shift variables are included. We note significant levels of autocorrelation in the regression residuals, with and without shift variables. These are much lower estimates of returns to scale than were found in historic literature for other economies. Solely to provide context (since direct comparison of results across studies is rarely possible due to different measures used for stocks and flows) we record that Blanchard and Diamond (1989) found evidence for constant returns to scale in United States data with elasticity of unemployment of about 0.35 in their most basic specification. Petrongolo and Pissarides (2001, p. 393) surveyed various studies, mostly of the United States and various European countries, and generally found support for constant returns to scale and claimed a plausible range for the elasticity of unemployment of 0.5-0.7. Our estimates of the coefficients of RR and FTE were not significant. $LTUR$ was significant in specifications (2) and (4) however, as noted above, it is likely that $LTUR$ is simply acting as a proxy for lagged U.

We cannot be sure why the estimates of return to scale are so much lower than prior estimates in other markets. We conjecture that it may relate to the high level of persistence in several of the variables in our sample, so that it may be inappropriate to try and measure returns to scale in the above manner without properly accounting for lagged responses. Significant evidence of autocorrelation in the residuals may also indicate that the functional form of equation (5) is not appropriate for our sample. In the next two sections we consider alternative specifications for the UV relationship.

4.4. Beveridge Curve representation of UV equilibrium

We make some simple observations which illustrate why it is difficult to fit the functional form of equation (5) to the sample data. The level of V was very low in absolute terms at the depth of the 1991 recession. Accordingly, relative changes (or absolute log differences) in V were extremely large for many periods surrounding this event, as we can observe in Figure 9. In relative terms, V nearly tripled in the three years following its lowest level in the recession, whereas U fell by only about 30% in the three years following from its peak in the same recession. However in the recent global financial crisis the major movements in log levels of U and V were of similar order of magnitude. Taken together these characteristics make it difficult to fit the log-log form with fixed elasticities.

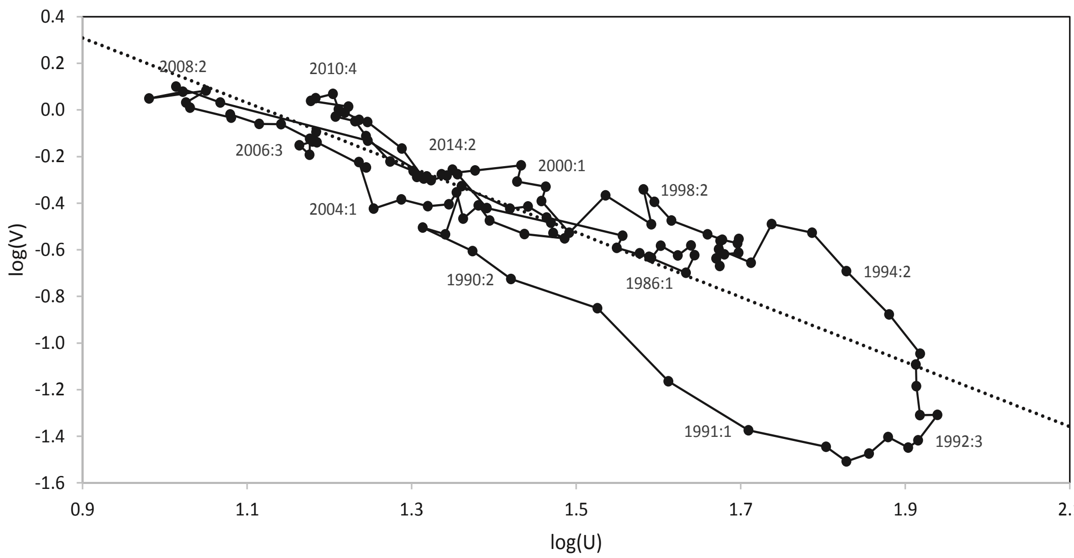
Figure 9. Log levels of unemployment rate and vacancy rate



Notes: Shaded periods indicate a contraction phase of the growth cycles.

This problem is manifested as a poor line of best fit (by ordinary least squares) in the scatter plot of shown in Figure 10. We can observe a prominent cycle in lower right hand corner of the figure due to the large cycle in $\log(V)$ relative to the cycle in $\log(U)$ arising from the 1991 recession. This empirical behaviour of $\log(V)$ and $\log(U)$ do not fit well with idealised behaviour expected under the Beveridge Curve theory. In an idealised case, business cycle variations shift V and U *along* a long run equilibrium locus represented by the Beveridge Curve. Other influences (ideally non-business cycle related) on search intensity or matching efficiency shift the curve left or right. We did not find that any of our trial shift variables were able to explain the behaviour in the 1991 recession.

Figure 10. Scatter plot of log(V) vs. log(U)



4.5. Stationarity of U and V

We briefly consider whether a cointegration framework would be appropriate to describe the relationship between U and V. A necessary condition for cointegration is that both U and V must be non-stationary. In Table 8 we show the results of an ADF test from which we cannot reject the null hypothesis that U and V are non-stationary. We note however that both variables are *rates*, since we have expressed them as a percentage of the Civilian Population. The rates are bounded by zero and one so they cannot be true random walks. It has been debated in the literature for many decades whether it is appropriate to treat the unemployment rate as a unit root process or a stationary process. The issue relates to a broader debate about competing theories for the existence of a natural rate of unemployment versus the existence of hysteresis, as discussed by Canarella, Miller and Pollard (2013). We prefer the view that the unemployment rate should be considered stationary in the long run. For completeness, in case our preferred view is wrong, we look at whether there is a simple cointegrating relationship between the pair of variables, as shown in Table 9. We performed an Engle-Granger cointegration test, both in levels and in log-levels, and in neither case did we find significant evidence of cointegration. We cannot exclude the possibility that a cointegrating regression could be formed from a larger group of non-stationary variables including U and V. Some other authors, notably Groenewold (2003), have had some success using this approach to define a Beveridge Curve relationship.

Table 8. Augmented Dickey-Fuller test

Variable	ADF const. tau-test	p-value	ADF const.+ trend tau-test	p-value
V	-1.60	0.483	-2.71	0.231
U	-1.92	0.323	-2.90	0.163

Notes: The null hypothesis is that the series is a unit root process.

Table 9. Cointegration tests

Variables	Cointegrating Regression with const. tau-test	p-value	Cointegrating Regression with const.+trend tau-test	p-value
U and V	-2.24	0.406	-2.24	0.661
$\log U$ and $\log V$	-2.08	0.485	-1.81	0.842

Notes: The null hypothesis is that the residuals from the cointegrating regression are non-stationary.

To summarise the preceding discussion of the UV relationship, we do not find a plausible linear relationship between V and U (in levels or log levels) that is invariant to the state of the business cycle. We did not find suitable shift variables to model the relationship with a standard model from Beveridge Curve theory. We also consider that imposing a cointegrating relationship between U and V (and potentially other variables) is likely to be misspecified. Instead we examine the possibility of an empirical long term relationship within an autoregressive model framework.

4.6. ARDL model of the UV relationship

We estimated a basic specification of an ARDL model with U as the dependent variable and V and Y as independent variables[23] as shown in equation (6). It is not certain that U belongs on the left hand side rather than V but we start here since theory prefers a model with V as an independent variable which is determined by firms in a forward looking manner. In our specification U can respond contemporaneously to V. We also allow the UV relationship to be affected directly by the business cycle variable.

$$U_t = \beta_0 + \beta_1 U_{t-1} + \beta_2 V_t + \beta_3 V_{t-1} + \beta_4 Y_t + \beta_5 Y_{t-1} + \varepsilon_t \qquad (6)$$

A regression summary for equation (6) is shown in Table 10.

Table 10. Regression summary

Equation	$U_t = \beta_0 + \beta_1 U_{t-1} + \beta_2 V_t + \beta_3 V_{t-1} + \beta_4 Y_t + \beta_5 Y_{t-1} + \varepsilon_t$						
			Independent Variables				
Constant	U_{t-1}	V_t	V_{t-1}	Y_t	Y_{t-1}	R^2	LM(4) p-val
0.943	0.875	-1.638	1.047	-0.063	0.003	0.989	0.001
(0.002)	(0.000)	(0.000)	(0.001)	(0.002)	(0.902)		

Notes: Coefficient estimates with p-values shown in parentheses, determined using HAC robust standard errors.

As indicated by the LM statistic there remains a high level of autocorrelation in the residuals despite the inclusion of lagged independent and dependent variables amongst the regressors. The AR(1) coefficient estimate is high (0.875) and the signs alternate on the coefficients for the contemporaneous and lagged terms of the other regressors. Together this indicates that first differences may have an important role to play in the relationship. Equation (6) was extended to include possible shift variables FTE and RR but neither were found to be significant explanatory variables.

Error correction models tend to be closely associated with cointegration analysis of non-stationary variables but they can also be applied to situations derived from an ARDL

[23] In this section we proceed under the assumption that all the variables are stationary.

model in stationary variables. Wickens and Breusch (1988) showed that there are numerous possible linear reformulations of a basic ARDL equation each of which may be useful to allow direct estimation of specific parameters of interest (and their standard errors) relating to either the long term relationship between the variables or to the short term dynamics. Reformulated equations may be expressed in a mixture of levels and first differences of the variables, including a formulation consistent with an error correction model.

Due to the high level of persistence in several of our variables we found it effective to specify an ARDL form with a first difference as the dependent variable as set out in equation (7). In using this structure we assume that there is no contemporaneous feedback from ΔU to ΔV. We will re-parameterise the equation after estimation into an error correction form. In essence equation (7) can be described as a single equation error correction model where the parameters for the long term relation and short term dynamics are estimated jointly. The regression summary for equation (7) is shown in Table 11.

$$\Delta U_t = \alpha + \beta_1 U_{t-1} + \beta_2 V_{t-1} + \beta_3 Y_{t-1} + \delta_1 \Delta U_{t-1} + \delta_2 \Delta V_t + \delta_3 \Delta V_{t-1} + \delta_4 \Delta Y_t + \delta_5 \Delta Y_{t-1} + \varepsilon_t \tag{7}$$

Table 11. Regression summary

Equation	$\Delta U_t = \alpha + \beta_1 U_{t-1} + \beta_2 V_{t-1} + \beta_3 Y_{t-1} + \delta_1 \Delta U_{t-1} + \delta_2 \Delta V_t + \delta_3 \Delta V_{t-1} + \delta_4 \Delta Y_t + \delta_5 \Delta Y_{t-1} + \varepsilon_t$									
			Independent Variables							
Constant	U_{t-1}	V_{t-1}	Y_{t-1}	ΔU_{t-1}	ΔVt	ΔV_{t-1}	ΔY_t	ΔY_{t-1}	R^2	LM(4)p-val
0.564	-0.075	-0.348	-0.031	0.236	-1.260	-0.276	-0.049	-0.044	0.584	0.064
(0.013)	(0.009)	(0.018)	(0.045)	(0.020)	(0.000)	(0.283)	(0.001)	(0.041)		

Notes: Coefficient estimates with p-values shown in parentheses, determined using HAC robust standard errors.

Inclusion of the short term dynamics in the equation has eliminated significant autocorrelation in the residuals (with a p-value of 0.064). All of the coefficient estimates are significant except the coefficient of ΔV_{t-1}, which we retain for simplicity.

Equation (8) is a re-parametrisation of equation (7) in error correction form[24], as follows:

$$\Delta U_t = \alpha - \theta(U_{t-1} - \gamma_1 V_{t-1} - \gamma_2 Y_{t-1}) + \delta_1 \Delta U_{t-1} + \delta_2 \Delta V_t + \delta_3 \Delta V_{t-1} + \delta_4 \Delta Y_t + \delta_5 \Delta Y_{t-1} + \varepsilon_t \quad (8)$$

where $\theta = -\beta_1$, $\gamma_1 = \beta_2 / \theta$ and $\gamma_2 = \beta_3 / \theta$. The parenthesised term describes the long term relationship between the variables (if it exists) and θ describes the rate of reversion towards the long term relationship. For the error correction form to be plausible we need the estimated value of θ to be greater than zero and significant. Using the results in Table 11 we find that $\theta = 0.075$, significant at 1%. We also find that $\gamma_1 = -4.61$ and $\gamma_2 = -0.42$. Another reformulation of equation (8) would allow direct estimation of the standard errors of γ_1 and γ_2 (Wickens & Breusch, 1988, p. 190) but we have not derived them. The error correction rate θ is of particular interest to us. Even if we allow that the term in parentheses represents an error correction term arising from a stable long term relationship then we observe that the relative rate of reversion towards this relationship is quite low, at 0.075 per period. This means that, ceteris paribus, it would take more than eight periods (two years) for half of the error to be corrected by the mechanism. Two years is a long time in the context of the propagation of business cycle shocks. We conjecture that the impact of the error correction mechanism on the dynamics is very likely to be dominated by other short term dynamics.

Equation (7) could have been specified with ΔV on the left hand side if we assumed that causation ran from U to V. In reality it is likely that there is two-way contemporaneous causation between U and V, but we do not have suitable instruments to solve this simultaneity problem completely. To provide some further validation of our previous observation about the low rate of error correction we re-estimated an equation of the form (7) with ΔV on the left hand side, as though causation ran from U to V. The estimation results were qualitatively similar to those we found with ΔU on the left hand side except with generally less significant coefficient estimates, a much lower R^2 and autocorrelation in the residuals significant at 5%. When the regression result was re-factorised into an error-correction form the point estimate of the

[24] Following Asteriou and Hall (2007, pp. 311-312) it can be shown that equations (7) and (8) are isomorphic to a standard ARDL specification with U_t as the dependent variable.

error correction rate was 0.131, significant at 5%. In short, the specification with ΔU on the left hand side appear to be more satisfactory but, in either case, we find a significant but low rate of error correction. Based on this result we will proceed to estimate a SVAR model which includes U and V as endogenous variables without attempting to impose a long run restriction on the relationship between them. Short term dynamics will be likely to dominate the relation between them. We can easily verify whether the impulse responses of the SVAR capture the strong negative empirical relationship that exists between U and V.

5. Mixed SVAR model of stocks and flows

We set up a SVAR model with a mixture of stocks and gross flows as endogenous variables. It seems highly likely that there would be two-way causal relationships between stocks and flows if the true underlying processes were known. By definition, gross flows to or from a stock A cause contemporaneous changes in the level of stock A. Theory does not provide a strong guide as to how a gross flow may also cause changes in the other stock variables to which it does not directly relate (such as the effect of eu on N) nor does it guide us to how lagged values of flows may affect stocks. In the other direction we expect lagged values of stock variables to affect gross flows. We have specified that the full period transition rate from generic state A to state B in period $(t+1)$ will be derived as $\lambda_{t+1}^{AB} = ab_{t+1} / A_t$, where ab_{t+1} is the gross flow of people during the period $(t+1)$ and A_t is the number of people in state A in the prior period. This can be expressed equivalently as $ab_{t+1} = A_t \lambda_{t+1}^{AB}$. In other words our definition implies that for a given level of λ_{t+1}^{AB} flows are directly proportional to the size of the originating pool of stock in the prior period, ceteris paribus.

We will use a recursive structure for the contemporaneous coefficient matrix in our SVAR and we will select an order of variables which places gross flows above the stock variables so that changes to gross flows can have a contemporaneous effect on stocks, but not vice versa. Lagged values of stocks can affect gross flows, so the system nests both of the possible causal relationships described above.

There are few examples in the literature which have applied a SVAR model to gross flows in the labour market. In a recent paper Dixon et al. (2015) use a SVAR model to analyse how shocks to *net* flows affect the evolution of the Australian unemployment rate and participation rate. In that paper the *net* flow from unemployment to employment is defined (using our variable names for gross flows) by $net\_ue = ue - eu$. By using net flows the number of variables and the dimension of the model is reduced, however the model is not capable of differentiating between (for example) job-separation shocks to eu and job-finding shocks to ue, which are of interest in our paper. A further distinguishing feature of our work is the use of a combination of stocks and flow variables in the model. Gross flows provide a direct expression of the dynamics of labour market stocks, but much of the economic theory is expressed in terms of *levels* of stocks (such as the levels of unemployment and vacancies). The SVAR model is atheoretical but allows for possible dynamic interactions between stocks and flows. One feature of our model in common with Dixon et al. (2015) is the use of identity relationships to generate the implied responses of other variables not included directly in the SVAR model, which we discuss further in section 5.2.

5.1. Discussion of stationarity

The Augmented Dickey-Fuller test was applied to all of the variables included in the model (except for Y which is stationary by construction) the results of which are shown in Table 12. We cannot reject the null hypothesis of non-stationarity for all variables except en and ne. As we noted earlier in relation to the unemployment rate, *all* of the gross flow and stock variables are rates since we have expressed them as a percentage of the Civilian Population. The rates are bounded by zero and one so cannot be true random walks. We prefer the view that our rates should be considered as being stationary in the long run whilst acknowledging that the data is likely to include unidentified cycles and trends that are operating at a much lower frequency than the business cycle, and possibly over a time period longer than our sample period. It is convenient then to follow a typical path taken in the literature of small macroeconomic VAR models and estimate the model in levels of the variables without differencing or de-trending even though some of the variables exhibit non-stationary behaviour in the sample period. The only exception is Y which, as previously described, has been de-trended with a Hodrick-Prescott filter to give a proxy for a business cycle indicator. For a relevant discussion of the issues of using non-stationary variables in VAR models see Enders (2009, p. 303).

Table 12. Augmented Dickey-Fuller Test

Variable	ADF const tau-test	p-value	ADF const + trend tau-test	p-value
V	-1.60	0.483	-2.71	0.231
E	-1.56	0.504	-3.11	0.104
U	-1.92	0.323	-2.90	0.163
eu	-1.30	0.632	-2.28	0.447
ue	-1.15	0.700	-2.35	0.408
ne	-3.46***	0.009	-3.53**	0.036
en	-3.19**	0.021	-3.17*	0.090
nu	-2.33	0.164	-2.64	0.261
un	-1.60	0.482	-2.50	0.328

Notes: The null hypothesis is that the series is a unit root process. Test results for the variables U and V are repeated from Table 8.

5.2. Selection of variables

We have four identities by which certain stocks and gross flows are related, as follows:

$$E + U + N = 100 \tag{I1}$$

$$\Delta E_t = E_t - E_{t-1} = ne_t + ue_t - en_t - eu_t \tag{I2}$$

$$\Delta U_t = U_t - U_{t-1} = nu_t + eu_t - un_t - ue_t \tag{I3}$$

$$\Delta N_t = N_t - N_{t-1} = en_t + un_t - ne_t - nu_t \tag{I4}$$

We cannot include all three of E, U and N as variables in the VAR model since they are related by the identity (I1). We will include E and U since they have the strongest theoretical links to other macroeconomic variables and are also likely to have the strongest empirical relationship between them. It is straightforward to determine the implied response of N using identity (I1) given impulse responses for E and U. By similar reasoning we should not include all six of the gross flows in a VAR model which already includes two of the stock variables and their lagged values since there are identity relationships between changes in stocks and gross flows as described by identities (I2)-(I4). We are careful not to include all four gross flow variables that go into or come out from a particular stock. We will include the set eu, ue, ne and nu in the model. We demonstrate in Appendix 2 that it is sufficient to have impulse responses for the two stocks and four gross flows named above to be able to determine implied impulses response for the remaining two gross flows that were excluded from the model.

The gross flows eu and ue were included since the flows between employment and unemployment are usually of most interest in labour market economics. We are left to choose one of the flows between U and N and one of the flows between E and N. There is no theoretical basis for choosing which flows to include so we were guided by empirical analysis. Cross-correlogram analysis of Hodrick-Prescott de-trended nu and un indicates that nu may lead un slightly, although the evidence is not compelling, which may indicate that nu has the more influential role of the pair. Similar analysis was conducted to compare the merits of including en or ne. The cross-correlogram points to fairly concurrent cyclical performance of the de-trended series. Foreshadowing later analysis of forecast error variance decomposition we trialled both en and ne and examined their contribution to the forecast error variance of U, which is of particular interest. Neither flow makes a significant contribution to the forecast error variance of U (both contribute less than 2% at most time horizons). This suggests that the choice of either is not of much significance to the model results and we have chosen arbitrarily to proceed with ne. Foreshadowing later analysis again, trials of different gross flow variables did not have a material impact on impulse responses generated by the model.

5.3. SVAR model

We will estimate a structural model of the form:

$$B(L)X_t = \varepsilon_t$$

X_t is a (8×1) vector of endogenous variables, L is the lag operator and $B(L) = B_0 - B_1L - B_2L^2 - ... - B_pL^p$ where the lag order is p. The matrix B_0 captures the coefficients for the contemporaneous interactions between the variables, and the matrices B_i capture the coefficients at lag i for $i > 0$. The structural errors ε_t have zero mean and are serially uncorrelated. The components of X_t and the order in which they are arranged and the structure of the matrix B_0 are shown in Figure 11.

Figure 11. Recursive contemporaneous coefficient matrix

$$B_0 X_t = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ b_{21} & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ b_{31} & b_{32} & 1 & 0 & 0 & 0 & 0 & 0 \\ b_{41} & b_{42} & b_{43} & 1 & 0 & 0 & 0 & 0 \\ b_{51} & b_{52} & b_{53} & b_{54} & 1 & 0 & 0 & 0 \\ b_{61} & b_{62} & b_{63} & b_{64} & b_{65} & 1 & 0 & 0 \\ b_{71} & b_{72} & b_{73} & b_{74} & b_{75} & b_{76} & 1 & 0 \\ b_{81} & b_{82} & b_{83} & b_{84} & b_{85} & b_{86} & b_{87} & 1 \end{pmatrix} \begin{pmatrix} Y_t \\ eu_t \\ ue_t \\ ne_t \\ nu_t \\ V_t \\ E_t \\ U_t \end{pmatrix}$$

5.4. Estimation with a recursive identification scheme

It is well known that by imposing a recursive structure on the contemporaneous coefficient matrix we can estimate the reduced form of the system using ordinary least squares working in order from the first row down to the last. The recursive structure also provides the condition for exact identification of the model so that we can recover the coefficients in B_0. A brief summary of the methodology for identifying and estimating a SVAR model is provided in Appendix 1.

5.5. Order of variables

The cyclical component of the output gap (represented by Y) has been used as a proxy for the business cycle indicator in the SVAR model so that we may directly measure the response of the labour market variables to unexpected shocks in the business cycle. We have placed Y in the first row the vector of variables based on the assumption that all the variables following in the order may respond contemporaneously to a business cycle shock. Y is endogenous in the model so that feedback of lagged responses of labour market stocks and flows can affect Y. As discussed in section 3.6, almost all of the labour market variables lag output by one or more periods so, whilst this may not necessarily reveal anything about the direction of causality, it provides empirical support for the placement of Y first in the order of variables.

As described earlier in section 5 the gross flow variables need to be placed above the stock variables. Next we consider the order of variables within the block of gross flows, then amongst the block of stock variables. Theory does not provide a guide to the ordering of the flows. It is reasonable to assume that both firms and individuals may make decisions about labour market movements based on forward looking as well as backward looking assessments. For example, firms may reduce hiring (which reduces ue and ne) or increase layoffs based on either an *expectation* that business conditions will weaken or an *actual* decline in conditions. Forward looking behaviour makes it plausible that there could be contemporaneous interactions between all of the variables but we do not have suitable instruments to properly identify the relationships between them. So we rely primarily on empirical analysis to support the order of the gross flow variables. In section 3.6 we found that eu has tended to lead all the other gross flows in our sample period so it is placed first amongst the gross flows. We place ue immediately after it to make any relation between the pair of them more obvious. The flow nu lags Y by more than ne so we have placed it last in the block. In summary we proceed with the order eu, ue, ne and nu[25].

In addition to employment and unemployment the block of stock variables will include the vacancy rate. The vacancy rate has been included since there is a long history of literature indicating that vacancies can play a significant role in the propagation of shocks through the labour market, in particular to the level and persistence of U. As described in section 4 it is possible that there is a two-way causal relationship between V and U which could include contemporaneous interaction between them. Theory suggests that changes in V will lead changes in U because firms choose the level of vacancies to supply in a forward looking manner. Analysis of business cycle characteristics in section 3.6 suggests that V leads U in our sample and that E leads U. We proceed with the order V, E and U[26].

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[25] We did not find that our impulse responses were sensitive to this ordering.
[26] As before, we did not find that our impulse responses were sensitive to this ordering.

Analysis of the UV relationship in section 4 did not reveal evidence of a robust long term relationship between levels of U and V. The evidence suggested that large swings in the business cycle do not merely generate shifts in U and V *along* the so called Beveridge Curve but instead that such swings can also shift the position of the curve. This precludes a reliable separation of business cycle effects from alternative institutional and search intensity effects during our sample period. Accordingly we have not attempted to impose any long run restriction on the relation between U and V in the SVAR model.

5.6. Alternative identification schemes

We considered a non-recursive structure for the matrix of contemporaneous coefficients, since we cannot exclude a number of possible two-way contemporaneous links between variables. However, to allow some free coefficients above the diagonal in the matrix would require some exclusion restrictions below the diagonal to ensure identification. There is no theoretical basis which we can use to justify exclusion restrictions between particular stocks and flows (or the business cycle variable). We tested some alternative restrictions suggested by empirical observations (i.e. restricting coefficients that had previously been estimated as small and statistically insignificant in the unrestricted model). However, we were unable to find an alternative scheme which produced materially different results so we will only present the results determined using the simple recursive scheme shown in Figure 11.

5.7. Reduced form regression diagnostics

5.7.1. Lag length selection

A variety of information criteria for optimal lag length selection indicated an optimal length of one or two periods. We use a likelihood ratio test to compare one lag against an alternative of two, and two against an alternative of three. The test statistic is:

$$(T-c)(\ln|\Sigma_R|-\ln|\Sigma_U|)$$

where Σ_R and Σ_U are the covariance matrices of the restricted and unrestricted regressions and the parameter c is a multiplier correction equal to the number of explanatory variables in each unrestricted equation (Doan, 2012, p. UG209). Test results are shown in Table 13, which provide support for the choice of two lags and we proceed with two in our model.

Table 13. Lag length testing

	Lag Length	Lag Length
H0*:	1	2
H1:	2	3
$\chi^2(64)$	104.77	72.54
significance	0.001	0.217

* The null hypothesis is that the regression coefficient is zero for the explanatory variables with the longer lag specified in the alternative hypothesis.

5.7.2. Autocorrelation in residuals

We tested the system for serial correlation of residuals using an LM test with up to 8 lags (Table 14). We could not reject the null hypothesis of no serial correlation for lags 1 to 7, whilst the 8th lag is significant at 10% but which we interpret as a purely random effect.

Table 14. Serial correlation tests (system)

VAR Residual Serial Correlation LM Tests
Null Hypothesis: no serial correlation at lag order h
Sample: 1986Q1 2014Q2
Included observations: 112

Lags	LM-Stat	Prob.
1	71.87194	0.2334
2	68.36806	0.3313
3	69.27176	0.3042
4	58.39232	0.6742
5	72.03283	0.2294
6	61.20922	0.5758
7	54.76592	0.7880
8	80.76113	0.0768

Probs. from chi-square with 64 df.

5.7.3. Normality of residuals

Residuals from the regression equations were found to be individually and jointly normal.

Table 15. Residual normality tests

VAR Residual Normality Tests - Joint
Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: residuals are multivariate normal
Sample: 1986Q1 2014Q2
Included observations: 112

Component	Jarque-Bera	df	Prob.
1	2.873891	2	0.2377
2	1.612575	2	0.4465
3	1.421097	2	0.4914
4	1.022767	2	0.5997
5	2.926118	2	0.2315
6	3.101763	2	0.2121
7	0.605488	2	0.7388
8	1.834408	2	0.3996
Joint	15.39811	16	0.4957

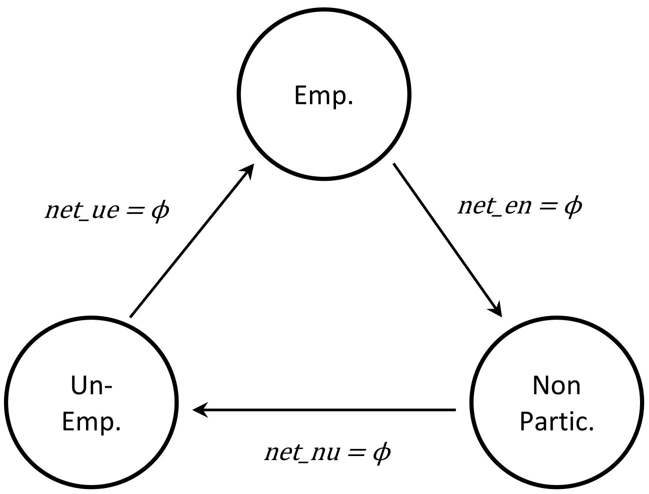
5.8 Initial conditions for steady state

A long run equilibrium value of the unemployment rate may exist but there is no solid theoretical basis from which to derive steady state values of the gross flows. Even with stock variables at steady state there need not be a unique solution for the gross flow variables. Flows reflect the aggregate level of mobility of the workforce which is not necessarily linked to stock levels. If the stocks and flows were in steady state together then we conjecture that the level of flows would reflect the prevailing level of mismatch in the labour market, the levels of search intensity by both workers and firms, and other unidentified factors.

For the purpose of analysing the SVAR model output it is convenient to define an equilibrium state and a set of initial conditions which would give rise to it. In particular it will allow us to derive the implied impulse responses for some variables not directly included in the SVAR model by using identity relationships to trace the responses of these variables starting from their initial steady state values. We define an equilibrium state as one in which the labour market stock variables are unchanged from one time period to the next, as illustrated in Figure 12. Each stock has four gross flows which affect it. The net inflow and net outflow from each stock must equate to maintain equilibrium. This does not define the level of individual gross flows since there are infinitely many combinations of each pair that can produce the same net flow.

Earlier in Figure 5(b) we showed that the sample mean quarterly net flows between each pair of states were quite similar at approximately 0.45% of Civilian Population per quarter. For initial conditions approximating a steady state equilibrium we set all of the included model variables to their sample mean values. We set the initial values of the excluded variables en and un to values slightly different to their sample mean values, derived to create the condition for steady state stock variables (with $\phi = 0.473$ in Figure 12). We need the initial values and impulse responses of all the stocks and flows so that we may derive implied impulse responses of the flow-rates, as previously defined in section 3.7. A complete table of initial values and sample mean values for each of the variables can be found in Appendix 3.

Figure 12. Equilibrium conditions defined



The equilibrium condition is defined by $\Delta E = \Delta U = \Delta N = 0$ between consecutive periods. Gross flows are not defined. The net flow between any two states in a period is ϕ ($\phi > 0$ corresponds with clockwise flows).

6. Estimation results

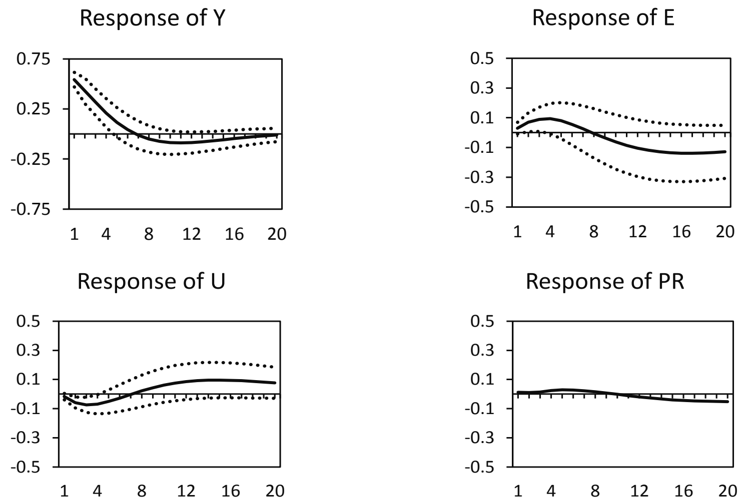
Parameter estimates are not provided here since individual parameter estimates typically have no direct interpretation when there are a large number of variables in a VAR model. We focus on interpreting the impulse response functions ('IRF's) of the variables to shocks to the structural errors, and look at a forecast error variance decompositions ('FEVD') (good explanations of these can be found in Enders (2009, pp. 307-315) and Hamilton (1994, pp. 318-324)). It is typical to plot the responses against the period index and to interpret the resulting IRF as the evolution of the dependent variable through time following a one-time shock in the first period.

6.1 Output shock

In Figures 13-15 we show impulse responses of selected model variables to a positive one standard deviation shock lasting for one period to the orthogonal error term in the first equation in the order set out in section 5.3 ('Y shock'). The response of Y (output gap) shows the inherent persistence that is typical in macroeconomic variables with the level of Y remaining above its equilibrium level for almost two years. E and U show procyclical and countercyclical responses, as expected, for about two years before reverting to and overshooting their initial equilibrium levels. We show the implied impulse response of the participation rate PR which has been derived using the appropriate identity relationship. The direction of the response of PR is consistent with procyclical behaviour but the magnitude is small. At most the response of PR could be described as weakly procyclical.

In Figure 14 we observe that the responses of en and ne are procyclical since they display positive responses for about the first two years, coinciding with the period of elevated output gap. This is in line with our expectation described earlier in section 3.6. The responses of un and nu both appear to be countercyclical, again in line with our earlier expectation, although the magnitude of the responses is low in absolute terms.

Figure 13. Impulse responses of stock variables: Y shock.



Notes: One standard deviation shock to the structural error term. Confidence bands are displayed at +/- 2 std. errors around the point estimates.

Figure 14. Impulse responses of gross flow variables: Y shock.

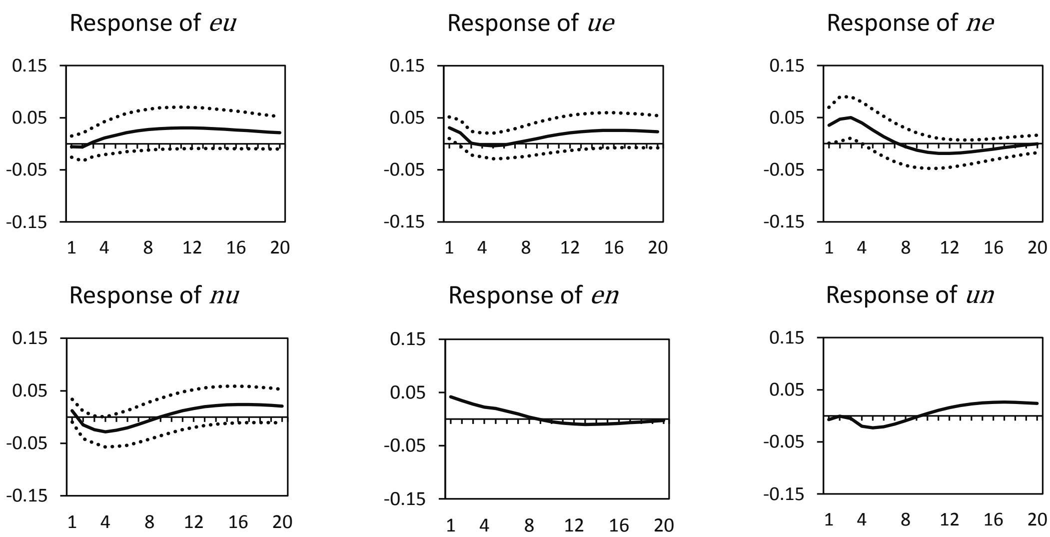
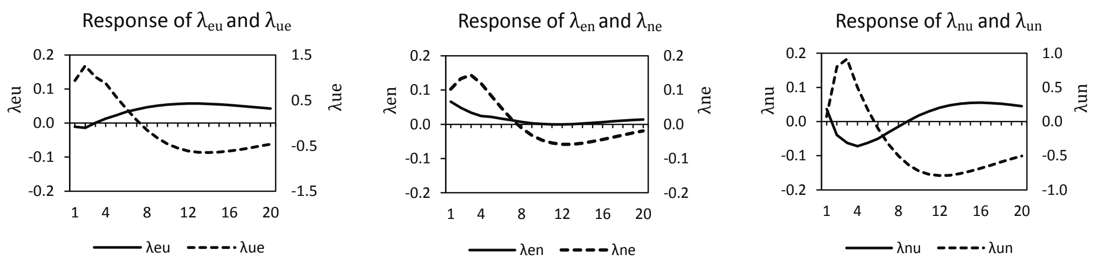


Figure 15. Implied impulse responses of flow-rates: Y shock.



The response of ue is positive for two periods but not significant for most of the first two years so its cyclicality is not clearly determined. Gross flow eu responds slowly in a positive direction over two years only becoming materially positive after the positive response of Y has eroded, so the cyclicality of the flow is not clearly determined. These findings contrast with the earlier analysis in section 3.6 which found that both of these gross flows were countercyclical.

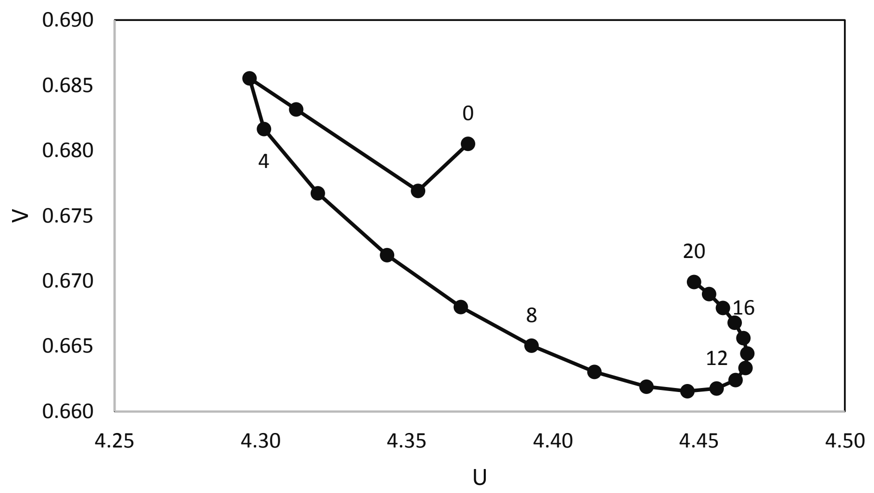
In Figure 15, we show derived responses of the flow-rates which are implied by the response paths of the relevant gross flows and stock variables. The job-finding rate (λ_{ue}) is elevated for two years in line with an intuitive response to a positive output gap, which we interpret as meaning that λ_{ue} is procyclical. The job-separation rate (λ_{eu}) falls initially by a negligible amount but then increases steadily. The rate does not become materially positive until the second year, during which time the initially positive responses of Y and E have eroded and are becoming negative. At most we could describe λ_{eu} as being weakly countercyclical. The job-finding rate certainly appears to be more responsive to the business cycle shock than the job-separation rate.

In Figure 15 we also find that the cyclicality of the flow-rates relating to non-participation are all consistent with our earlier expectation based on preliminary analysis as set out in Table 5. For example, λ_{ne} rises in response to a positive business cycle shock which lasts about eight periods so the empirical evidence is that λ_{ne} is procyclical. To summarise, we find that each of λ_{en}, λ_{ne} and λ_{un} are procyclical whilst λ_{nu} is countercyclical. These results are consistent with AWE being dominant for λ_{en}, λ_{nu} and λ_{un} whilst DWE is dominant for λ_{ne}, according to the definitions set out in Table 4.

6.1.2 Empirical UV relationship

We have included the vacancy rate V amongst the endogenous variables because of the prominent role it occupies in the literature which attempts to explain the rate of propagation of shocks through the labour market. We have not imposed a long run restriction on the relationship between U and V but we find that the empirical model results are strongly consistent with qualitative behaviour predicted by Beveridge Curve theory. In Figure 16 we see that the positive business cycle shock (and subsequent dynamic responses of the endogenous variables) generates a locus of points in UV space which describe a counter-clockwise loop around an apparent negatively sloping relationship between U and V. The rate of convergence is slow towards the end of the 20 periods. We would not argue that failure of U and V to return to their precise initial values within 20 periods was evidence of hysteresis. Broadly speaking we would characterise the responses as being consistent with a stable system. A discussion of the theoretical foundations for the looping behaviour can be found in Cahuc and Zylberberg (2004, pp. 547-548) and Blanchard and Diamond (1989, pp. 12-14). A discussion of empirical observations of this behaviour can be found in Rodenburg (2011, pp. 142-144).

Figure 16. Scatter plot of UV impulse responses: Y shock



Notes: The response path of the variables has been determined by adding impulse responses to the initial values of the variables set for equilibrium. The SVAR model shock has been applied in period 1 and the path traced for periods 0 to 20 (quarters).

6.2 Gross flow shock: job-loss

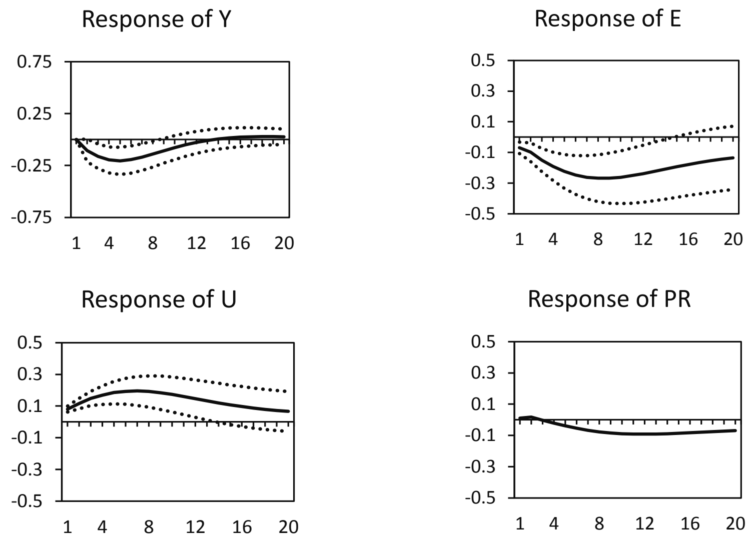
We can also induce a change in the business cycle by applying a shock to the error term for one of the equations with a gross flow or stock variable on the left hand side. Since stock variables are changed directly by flows it is more intuitive to apply a shock to a gross flow and allow the model to determine the impact of the shock on the stock variables due to contemporaneous and lagged responses to flows. In particular we apply a positive shock to the error term in the eu equation. An interpretation of this shock is an unexpected increase in the number of workers separating from employment and flowing into unemployment. Implicitly, each of these additional workers separating from employment must have decided to remain in the labour force and hence are classified as unemployed rather than non-participating. An obvious example scenario in the real world which corresponds to this shock is one in which there is a large unexpected layoff of workers, perhaps responding to an industry shock or other exogenous shock which is not represented explicitly in our model.

In Figure 17 we see that there is a high level of amplification and persistence of the eu shock. Both E and U show an anticipated contemporaneous response to the increased flow from E to U but we observe that the peak response of each is only achieved after about eight periods and which declines only slowly thereafter. Feedback from the labour market variables induces a negative response in the business cycle indicator Y which lasts for about 12 periods.

There is a slow but clear negative response in the participation rate which is maximised after about three years. The participation rate exhibits lagged positive co-movement with the business cycle indicator consistent with our expectations based on earlier analysis in section 3.6. This evidence supports the earlier finding that PR is procyclical.

The eu shock has induced a negative response in the business cycle proxy variable so next we consider the cyclicality of the gross flows by the characteristics of their responses to this negative change in the business cycle. Accordingly we see in Figure 18 that the responses of eu and ue are countercyclical since they have tended to rise when the business cycle indicator has fallen. Similarly, nu and un are found to be countercyclical and en and ne are procyclical, all as expected.

Figure 17. Impulse responses of stock variables: eu shock



Notes: One standard deviation shock to the structural error term. Confidence bands are displayed at +/- 2 std. errors around the point estimates.

Figure 18. Impulse responses of gross flow variables: eu shock

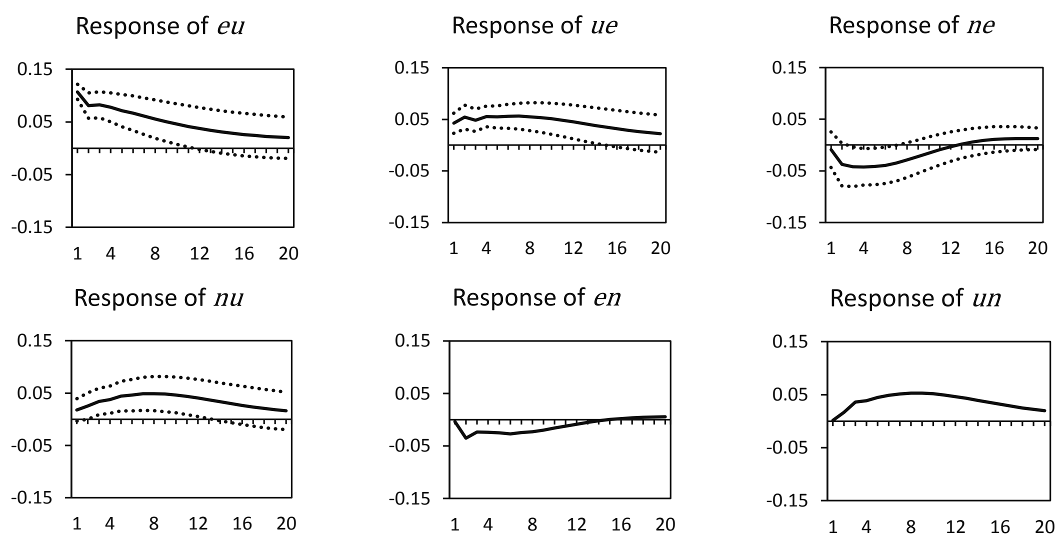
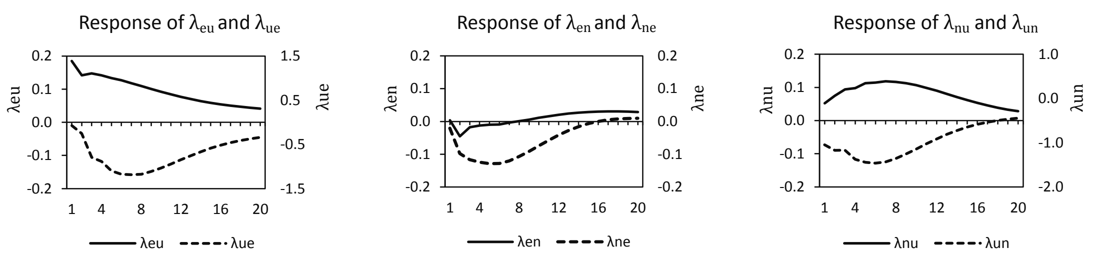


Figure 19. Implied impulse responses of flow-rates: eu shock

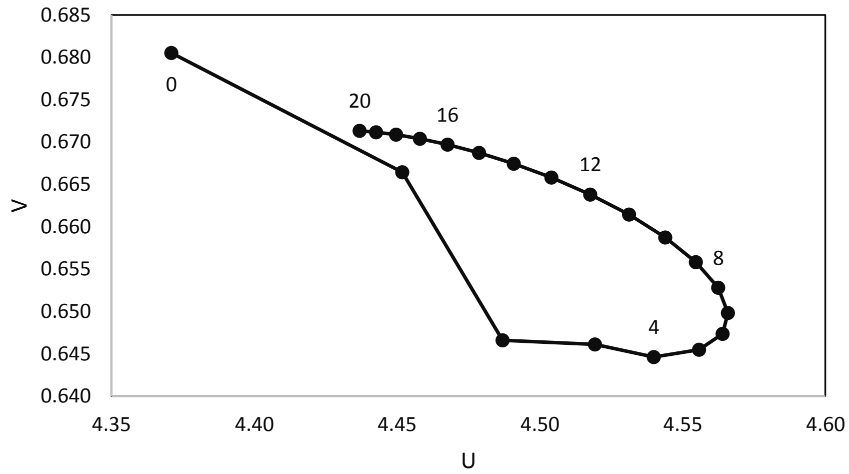


In Figure 19 we can see the job-separation rate (λ_{eu}) jumps initially (by construction, since we have applied a positive shock to eu) and that the elevated rate persists to some degree for at least 20 periods. The shock has also induced a large fall in the job-finding rate λ_{ue} which only reaches its low after about two years. Since the business cycle response has been negative we describe the response of λ_{eu} as countercyclical and the response of λ_{ue} as procyclical. Our result demonstrates a high level of endogenous interaction between the two rates. This may be due to more than the simple mechanical relationship which we have used to derive flow-rates. Elsby et al. (2009, p. 105) observed that in the real underlying model there may be a congestion effect whereby a sudden large influx of workers into the unemployment pool could cause outflow rates to fall. Cyclical changes in the composition of the inflow to unemployment may have a negative impact on average search intensity or effectiveness of those in the pool. This highlights the potential difficulty of attempting to separate the causal influences of the job-finding and job-separation rates on the other variables such as the unemployment rate.

Finally we consider the cyclicality of the flow-rates relating to non-participation in Figure 18. Once again we do this in the context of the positive eu shock having induced a negative business cycle response. For example, λ_{ne} falls in response to the negative business cycle so the empirical evidence is that λ_{ne} is procyclical. λ_{en} appears to be weakly procyclical. λ_{un} and λ_{nu} are procyclical and countercyclical respectively. In summary, the cyclicality of all of the flow-rates that we have determined from the responses to the eu shock are consistent in direction with the cyclicality determined from the Y shock but the strength of the responses vary.

In Figure 20 we see that the shock has once again generated counter-clockwise looping behaviour in the UV locus with slow convergence towards the initial values. These results give a level of confidence that the SVAR model has captured an important part of the dynamic behaviour which search and matching theory seeks to explain.

Figure 20. Scatter plot of UV impulse responses: eu shock



Notes: The response path of the variables has been determined by adding impulse responses to the initial values of the variables set for equilibrium. The SVAR model shock has been applied in period 1 and the path traced for periods 0 to 20 (quarters).

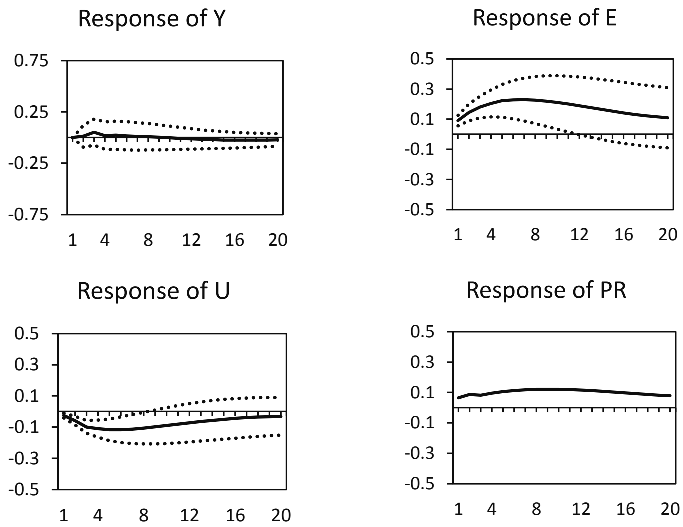
6.3 Gross flow shock: job-finding

The net flow between employment and unemployment will also be affected by a shock to the number of unemployed workers finding jobs. We apply a positive shock to the error term in the ue equation. It is more difficult to make a clean interpretation of this shock in the real world. A positive shock could reflect a sudden increase in employment via the creation of *new* jobs which are filled by previously unemployed persons. Equally it could reflect the implementation of a government program to increase the level of matching of unemployed workers with *existing* job openings, whether or not they have been advertised as vacancies.

In Figure 21 we see that the shock has a persistent effect on the levels of employment, unemployment and the participation rate, consistent with a positive change in the business cycle, but that it does not induce a significant response in the output gap. This makes it difficult to interpret the cyclicality of the flow-rates in Figure 23 in the absence of a material response in the business cycle indicator[27].

[27] Some studies of the cyclical behaviour of labour markets, such as Ponomareva and Sheen (2010), use the employment to population ratio directly as the business cycle indicator.

Figure 21. Impulse responses of stock variables: ue shock



Notes: One standard deviation shock to the structural error term. Confidence bands are displayed at +/- 2 std. errors around the point estimates.

Figure 22. Impulse responses of gross flow variables: ue shock

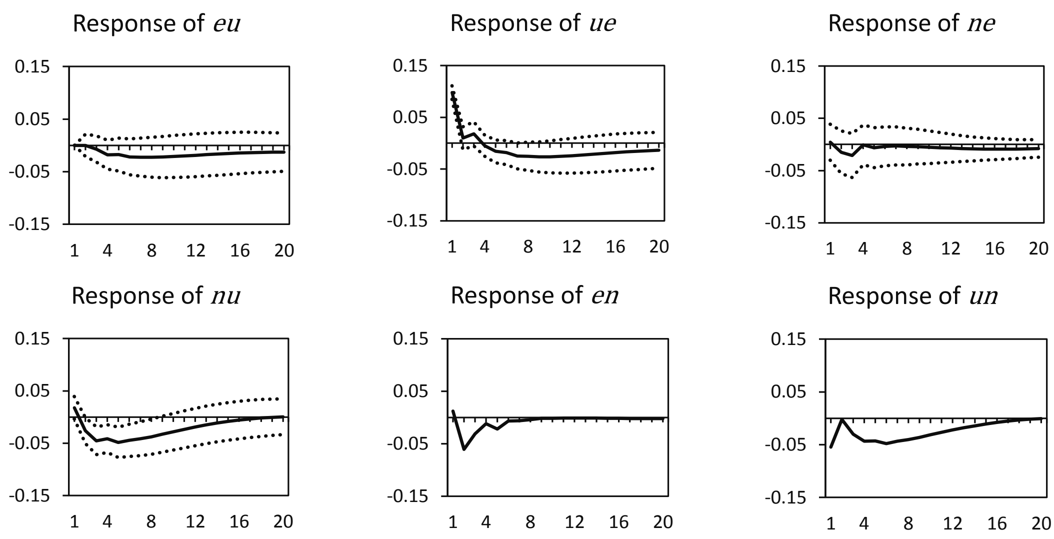
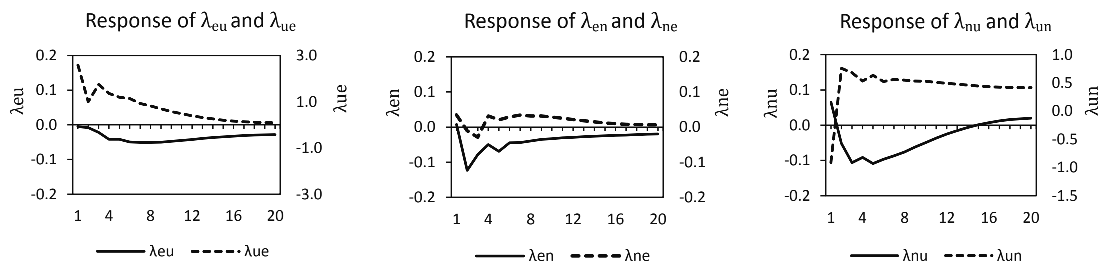


Figure 23. Implied impulse responses of flow-rates: ue shock.



6.4 Flows contributing to unemployment

We have found that both job-separation and job-finding shocks induce an amplified and persistent response in unemployment but we cannot easily attribute a causal influence to either due to endogenous interaction with other model variables. We can get another insight into the relative importance of the flows eu and ue by observing the contribution they each make to the forecast error variance of other variables and of each other. Selected outputs from a FEVD are shown in Table 16 which indicate the proportion of forecast error variance of each variable due to each of the shocks. We observe that the eu shock explained 44.4% of the forecast error variance of ue after 20 periods, whilst the attribution vice versa was only 4.9%. This result will depend on the order of variables, with variables placed earlier in the order tending to be more influential, ceteris paribus. We produced the FEVD again having reversed the order of eu and ue. Full results are not shown here but we found that after 20 periods eu explained 47.6% of the forecast error variance of ue whilst the attribution vice versa was only 3.6%, i.e. the result is not materially different from the prior result. Earlier in section 3.6 we found that cyclical changes in eu lead cyclical changes in ue by two or three periods. Together these results provide a strong indication that eu is a more influential variable than ue.

It has been of particular interest in the literature to compare the influence of inflows and outflows to the unemployment rate as discussed in section 3.7.2. Our results for the forecast error variance decomposition of U are not directly comparable with the previously referenced work since our explanatory variables are the gross flows rather than the transition rates. However, in Table 16, we observe that eu contributes approximately three times as much to the forecast error variance of U as does ue at all times beyond four periods. We try some alternative selections and orderings of the variables to see if the relative importance of inflows and outflows to unemployment is robust to the changes. In the first panel in Table 17 we changed the variables ne and nu to en and un respectively. Note that this version of the model has two outflows from unemployment (ue and un) whereas the previous version had only one. The combined forecast error variance of U due to outflows (ue and un) is still substantially lower than that due to inflows (eu) at all time horizons. In the second panel in Table 17 we changed the order of the variables ue and eu. The combined forecast error variance of U due to outflows (ue) is less than 2% at all time horizons, substantially lower than that due to inflows ($eu+nu$).

We also consider the relative contribution to U made by flows which affect participation (namely flows between U and N) with those between U and E. In Tables 16 and 17 we observe that, for all of the variable orderings shown, the flows between U and N make some contribution to the variance of U (more than 10% in some cases) but always materially less than the combined contributions of the flows between E and U.

Table 16. Forecast error variance decomposition

Decomposition of eu

Period	S.E.	Y	eu	ue	ne	nu	V	E	U
1	0.11	0.3	99.7	0.0	0.0	0.0	0.0	0.0	0.0
4	0.19	0.6	89.5	1.1	0.3	1.3	3.8	2.6	0.9
8	0.25	3.6	75.4	3.5	0.2	2.0	8.5	4.0	2.8
12	0.29	6.9	64.0	4.5	0.4	5.5	10.1	3.9	4.8
16	0.32	8.8	56.9	4.7	0.6	9.2	10.5	3.4	5.8
20	0.34	9.8	52.9	4.9	0.6	11.6	10.8	3.1	6.2

Decomposition of ue

Period	S.E.	Y	eu	ue	ne	nu	V	E	U
1	0.11	7.7	14.7	77.6	0.0	0.0	0.0	0.0	0.0
4	0.15	6.0	43.3	42.7	2.6	1.0	1.7	1.3	1.5
8	0.20	3.5	54.8	28.9	1.6	0.8	6.4	1.8	2.1
12	0.25	4.1	53.2	23.9	1.2	1.9	10.0	2.2	3.4
16	0.28	6.4	48.4	20.7	1.2	5.1	11.3	2.2	4.7
20	0.30	8.2	44.4	18.8	1.3	8.2	11.6	2.0	5.5

Decomposition of U

Period	S.E.	Y	eu	ue	ne	nu	V	E	U
1	0.12	2.1	47.7	4.6	4.8	7.9	1.1	0.8	30.9
4	0.37	10.5	52.2	19.2	0.8	4.4	4.5	0.5	7.8
8	0.62	4.7	55.7	19.9	0.6	1.9	9.1	2.4	5.8
12	0.80	5.7	50.9	16.7	1.0	4.1	10.8	3.7	7.2
16	0.92	8.5	44.7	14.0	1.3	8.6	10.8	3.7	8.6
20	1.00	10.1	40.7	12.5	1.3	12.3	10.6	3.3	9.2

In summary we find that the inflow of workers to unemployment, particularly those arriving from employment, are much more significant to the unemployment rate[28] than

[28] The unemployment rate as a percentage of Civilian Population.

the outflow from unemployment to either employment or non-participation. This result is counter to findings in some previous research, typically in the United States, that unemployment outflow rates are more important than unemployment inflow rates to the variance of unemployment, as described in section 3.7.2. In Australia our result is in broadly line with Ponomareva and Sheen (2010) who found that job-losing was more important than job-finding for their full sample period which included the 1991 recession (as does our sample). Our finding that the unemployment rate is influenced much more strongly by flows between unemployment and employment than flows involving participation decisions is also broadly in line with the findings of other authors in Australia (Ponomareva & Sheen, 2010, pp. 45-46) and in the United States (Barnichon & Figura, 2012, p. 25). However, our SVAR based methodology is quite different to the typical methodology used in the previously referenced literature, which has tended to construct a decomposition of the historic unemployment rate based on a theoretical structural relationship between the steady state unemployment rate and state transition rates. We observe also that our results apply to data which has been aggregated at a high level which may mask offsetting relationships between different sub-groups of workers which could be evident in more granular data.

Table 17. Forecast error variance decomposition - alternative variable ordering

Decomposition of *U*

Period	S.E.	*Y*	*eu*	*ue*	*en*	*un*	*V*	*E*	*U*
1	0.11	4.0	50.0	3.1	2.6	1.5	2.4	2.9	33.5
4	0.35	12.1	51.5	13.9	0.6	1.1	6.2	1.2	13.3
8	0.62	4.9	52.7	12.1	0.9	4.8	9.8	4.8	9.9
12	0.82	7.6	46.7	8.4	1.2	10.0	10.4	7.1	8.7
16	0.95	12.3	40.2	6.3	1.6	14.5	10.1	7.2	7.7
20	1.02	15.2	36.3	5.4	2.1	17.5	9.8	6.7	6.9

Decomposition of *U*

Period	S.E.	*Y*	*ue*	*eu*	*ne*	*nu*	*V*	*E*	*U*
1	0.12	2.1	0.6	51.8	4.8	7.9	1.1	0.8	30.9
4	0.37	10.5	1.7	69.8	0.8	4.4	4.5	0.5	7.8
8	0.62	4.7	1.4	74.2	0.6	1.9	9.1	2.4	5.8
12	0.80	5.7	1.0	66.6	1.0	4.1	10.8	3.7	7.2
16	0.92	8.5	0.7	57.9	1.3	8.6	10.8	3.7	8.6
20	1.00	10.1	0.6	52.5	1.3	12.3	10.6	3.3	9.2

7. Conclusion

We have measured the business cycle characteristics of labour market stocks, gross flows and flow-rates using a SVAR model. The model is able to replicate important empirical characteristics of the market that have been observed by other authors such as a procyclical job-finding rate and a weakly countercyclical job-separation rate. The model exhibits dynamic joint behaviour of unemployment and vacancies which appears to be consistent with expectations based on theoretical models of the UV relation.

We find evidence that the total labour force participation rate is procyclical which is consistent with a Discouraged-Worker Effect which dominates the Added-Worker Effect in aggregate. By using gross flow data rather than net flow data we are able to derive separately the cyclical characteristics of flows in both directions between each pair of labour market states. We find evidence that the flow-rate from non-participation to employment is procyclical (decreased participation in a recession) which is consistent with the Discouraged-Worker Effect, whereas the other three flow-rates that directly affect participation are consistent with the Added-Worker Effect (increased participation in a recession). Further research with more granular data may reveal whether this behaviour is consistent amongst different sub-groups of workers.

We find that inflows to unemployment are more important than outflows to the evolution of unemployment, and that flows between unemployment and employment are much more important than flows in or out of the labour force. This result has implications for policy initiatives which seek to reduce unemployment by showing the higher relative importance of measures designed to reduce job-loss compared to measures designed to create new hires.

Appendices

Appendix 1. SVAR Model

We define the following representation of a p^{th} order VAR in reduced form (with the constant term omitted for convenience)[29]:

$$X_t = A_1 X_{t-1} + A_2 X_{t-2} + \ldots + A_p X_{t-p} + u_t$$
$$\mathrm{E}\left[u_t u_t'\right] = \Omega$$
$$\mathrm{E}\left[u_t u_{t+s}'\right] = 0, \forall s \neq 0$$

where X_t is a $(k \times 1)$ vector of endogenous variables at time t, A_i is a $(k \times k)$ matrix of regression parameters on the i^{th} lagged variable and u_t is a $(k \times 1)$ vector of reduced form errors with zero mean. The errors u_t are serially uncorrelated and there are no restrictions on the form of the variance-covariance matrix Ω. We can condense the representation of the VAR by using lag operator notation (L) and introducing a p^{th} order matrix polynomial in the lag operator, $A(L) = I - A_1 L - A_2 L^2 - \ldots - A_p L^p$, so that we can express the reduced form VAR equation as:

$$A(L) X_t = u_t \tag{1}$$

We postulate that the reduced form arises from a true structural form that includes contemporaneous interactions between some of the variables. We can represent the SVAR model as:-

$$B(L) X_t = \varepsilon_t \tag{2}$$

where $B(L) = B_0 - B_1 L - B_2 L^2 - \ldots - B_p L^p$. The parameter B_0 captures the contemporaneous interactions between the variables. The structural errors ε_t have zero mean and are serially uncorrelated. We place a restriction which requires the errors to be mutually orthogonal, so that their variance-covariance matrix is diagonal:

$$E\left[\varepsilon_t \varepsilon_t'\right] = D$$

[29] We follow a presentation format similar to Berkelmans (2005). See also Chapter 11 in Hamilton (1994).

Orthogonality allows us to make a meaningful interpretation of ε_t as 'structural disturbances' and equation (2) as a structural model. An appropriate choice of the structure of the matrix B_0 can yield a system where each of the structural disturbances has a contemporaneous effect on only one of the equations in the system.

If we assume that B_0^{-1} is invertible then we can reduce the structural form into the reduced form described in equation (1) by pre-multiplying equation (2) by B_0^{-1} and defining $A(L) = B_0^{-1}B(L)$ and $u_t = B_0^{-1}\varepsilon_t$ so that

$$A(L)X_t = u_t$$

We have the following relationship[30] between the variance-covariance matrices of ε_t and u_t:

$$\Omega = B_0^{-1}DB_0^{-1\prime} \tag{3}$$

We want to estimate the elements of D and B_0 but a number of exclusion restrictions need to be applied to B_0 for the system to be identified. Since Ω is a square and symmetric $(k \times k)$ matrix it contains only $(k^2+k)/2$ distinct elements. D contains k distinct elements and unrestricted B_0 a further k^2, together making k^2+k. For the structural errors to be exactly identified we need a total of $(k^2+k)/2$ distinct elements on both sides of (3), so we need to add $(k^2+k)/2$ restrictions to B_0. One way of achieving exact identification is to impose a lower triangular structure on B_0 with 1's along its principal diagonal and zeros above it. We may easily verify that this has imposed the necessary number of restrictions. This form of restriction creates what is known as a recursive VAR. Working from the first row downwards each equation can be estimated separately by OLS since the right hand side variables comprise only lagged

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[30] $\Omega = E\left[u_t u_t'\right] = E\left[B_0^{-1}\varepsilon_t(B_0^{-1}\varepsilon_t)'\right] = B_0^{-1}E\left[\varepsilon_t\varepsilon_t'\right]B_0^{-1\prime} = B_0^{-1}DB_0^{-1\prime}$

terms or contemporaneous terms which were estimated in a previous row and thereby circumventing the problem of simultaneity.

If we are employing a recursive VAR then we can use a Cholesky factorisation to solve (3) easily (Hamilton, 1994, pp. 87-92). Since Ω will be a symmetric positive definite matrix there will exist a unique factorisation $\Omega = PP'$ and the closely related triangular factorisation $\Omega = \Sigma D \Sigma'$. In the latter form Σ is a lower triangular matrix with 1's along the principal diagonal and D is a diagonal matrix with positive entries along the diagonal. The relationship between the two forms is simply $P = \Sigma D^{1/2}$, where the Cholesky factor P has the square root of the corresponding elements of D along its diagonal. Algorithms for calculating P and thence Σ and D are well known and available in commercial software. By replacing Σ with B_0^{-1}, so $\Omega = B_0^{-1} D B_0^{-1\prime}$, we can see that we have a solution for (3) and we can invert B_0^{-1} to recover the matrix of contemporaneous coefficients.

Appendix 2. Implied impulse responses for excluded variables

Suppose that we have specified initial values at time t_0 for each of the variables in the SVAR as well as the excluded variables N, en and un. If the impulse (shock) is applied to the model in the period following t_0 then the SVAR model impulse responses would give us the values of E_{t_0+1}, U_{t_0+1}, eu_{t_0+1}, ue_{t_0+1}, ne_{t_0+1} and nu_{t_0+1}. Identity (I1) can then be used to determine N_{t_0+1}. Changes in the stock variables ΔE_{t_0+1}, ΔU_{t_0+1} and ΔN_{t_0+1} can be easily determined. Then identity (I3) can be used to determine un_{t_0+1}, and (I4) can be used to determine en_{t_0+1}. The same process can be used to determine the implied responses of un and en for all subsequent periods in the analysis. We can also determine the implied impulse responses of each of the derived flow-rates, e.g. λ_{nu} can be determined from the responses of nu and N since $\lambda_{nu,t} = nu_t / N_{t-1}$. Confidence bands for impulse responses will only be available for the variables included directly in the SVAR model.

Appendix 3. Initial conditions for steady state

Initial values of variables for steady state equilibrium.

Variables	Sample Mean	Initial Value for Equilibrium
E	59.343	59.343
U	4.371	4.371
V	0.681	0.681
eu	2.008	2.008
ue	2.481	2.481
ne	4.662	4.662
nu	3.091	3.091
Derived variables		
N	36.286	36.286
PR	63.714	63.714
en	5.090	5.135
un	2.628	2.618
net_ue	0.473	0.473
net_en	0.428	0.473
net_nu	0.463	0.473
λ_{eu}	3.384	3.384
λ_{ue}	56.763	56.763
λ_{en}	8.577	8.653
λ_{ne}	12.848	12.848
λ_{nu}	8.518	8.518
λ_{un}	60.119	59.888

Appendix 4. Data sources and definition of variables

Symbol	Description
CP	Civilian Population (aged 15 years and over); Persons. Quarterly series created by taking the average of monthly series. Source ABS cat. no. 6202.
V	Vacancy rate as a percentage of CP. Derived from Job Vacancies; Australia; s.adj. Source ABS cat. no. 6354. Five missing values in 2008-09 were interpolated using a quintic spline.
V_{-1}	Level of V in the prior period.
ΔV	First difference in V.
ΔV_{-1}	First difference in V in the prior period.
E	Employment rate as a percentage of CP, from Employment to Population ratio; Persons; s.adj., ABS cat. no. 6202, viewed 30 January 2015. Quarterly series created by taking the average of monthly series.
PR	Participation Rate as a percentage of CP, from Participation Rate; Persons; s.adj. ABS cat. no. 6202, viewed 30 January 2015. Quarterly series created by taking the average of monthly series.
u_rate	(Conventional) unemployment rate as a percentage of Labour Force. Unemployment rate; Persons; s.adj. ABS cat. no. 6202, viewed 30 January 2015. Quarterly series created by taking the average of monthly series.
U	Unemployment rate as a percentage of CP. Also known as 'Unemployment to population ratio'. Derived from the relation $U = u\_rate \times PR / 100$
LF	Labour Force. Sum of employed and unemployed persons, both s.adj.
N	Non-participation. Non-participating persons as a percentage of CP. $N = 100 - PR$
Y	Cyclical component of ln(GDP) using Hodrick-Prescott filter with λ=1600. GDP is real Gross Domestic Product, chain volume, s.adj. Quarterly series. Source Reserve Bank of Australia series ID GGDPCVGDP.
u_ben	Over 21 years single unemployment benefit and sickness benefit (real). Quarterly series created by taking average of monthly snapshots of the prevailing benefit. Source http://guides.dss.gov.au/guide-social-security-law/5/2/1/20. Real benefit calculated by deflating the nominal benefit using Reserve Bank of Australia quarterly measure of trimmed mean inflation, s.adj.
RR	Replacement Ratio = Real Wage Price Index / u_ben A continuous independent series of the Wage Price Index was not available for the full sample period. We spliced together a series from several sources including:- Wage Price Index; Australia; ordinary time hourly rates of pay excluding bonuses; private and public; all industries, source ABS cat. no. 6345, Sep.1997-June 2014; Average Weekly Earnings; Persons; Full Time; Adult; Ordinary Time Earnings; All Industries, source ABS cat.no. 6302, Feb.1986-June1997, including manual capture from original reports

	without adjustment for the sub-period Feb.1986-May1994. Real wage price calculated by deflating the nominal wage price using Reserve Bank of Australia quarterly measure of trimmed mean inflation, s.adj.
LTUR	Long term unemployment ratio = proportion of unemployed who have been unemployed for 52 weeks or more, expressed as a percentage. From Long-term unemployment ratio; Persons; s.adj.; ABS cat.no 6291.0.55.001. Quarterly series created by taking average of the monthly series.
FTE	Ratio of full-time employed persons to total employed persons (full time + part time). From Employed - full-time; Persons; s.adj. and Employed – part-time; Persons, s.adj. Source ABS cat. no. 6202. Quarterly series created by taking average of the monthly series.
Gross Flow	Seasonally adjusted aggregate quarterly gross flow of persons between two labour force states, using gross changes in stocks derived from matched records. Original monthly series ABS Cat 6202, data cube GM1 from August 1991. Data prior to August 1991 from ABS cat.no. 6203. The original data was transformed to make the flows approximately consistent with changes in corresponding stock data series using the process developed by Dixon et al. (2004). Some missing flows were estimated by interpolation taking into account seasonality. The transformed data was then seasonally adjusted and the monthly series compressed into a quarterly series by simple aggregation.
en	100 x Gross Flow from Employment to Non-participation/CP
ne	100 x Gross Flow from Non-participation to Employment/CP
nu	100 x Gross Flow from Non-participation to Unemployment/CP
un	100 x Gross Flow from Unemployment to Non-participation/CP
eu	100 x Gross Flow from Employment to Unemployment/CP
ue	100 x Gross Flow from Unemployment to Employment/CP
λ_{eu}	100 x eu/E 'Flow-rate' or 'full period transition probability'
λ_{en}	100 x en/E
λ_{ue}	100 x ue/U
λ_{un}	100 x un/U
λ_{nu}	100 x nu/N
λ_{ne}	100 x ne/N

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