The UK labour force participation rate: business cycle and trend influences

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Abstract

In this paper the extent to which recent patterns in UK labour force participation have been influenced by trend and business cycle factors is investigated. A modelling strategy is proposed that pools the available micro and aggregate-level data, to produce a mutually consistent model of the trend and cyclical components of participation. A significant procyclical pattern is established, but some distinct trend influences on the participation rate are also identified. The approach allows for the construction of forecasts, which would be a useful input into the sort of macroeconometric models used by policymakers. The model outperforms some conventional macroeconometric forecasts in out-of-sample forecast tests.

Key words: Participation, business cycles, micro trends.

JEL classification: E32, E24, E27.

Summary

Policymakers will frequently be interested in how ‘tight’ the labour market is currently and how tight it can be expected to be in the future. This assessment will in turn depend upon a view of how the demand for labour compares with its availability. Looking at the unemployment rate alone might not be a sufficient statistic for gauging labour availability, since the inactive population represents a large potential source of labour supply. And the distinctions between some forms of inactivity and unemployment can be fairly weak, so that certain types of inactive people are as likely to fill jobs as the unemployed.

The decision whether to participate in the labour market is subject to numerous long-term ‘trend’ influences. In the United Kingdom, these long-term influences have included an increase in the number of students, as well as in the number of individuals who report themselves as long-term sick. But alongside these trend influences some aggregate business cycle effects are also likely to operate.

This paper investigates the extent to which the participation rate is influenced by structural trends and by the business cycle. We propose a modelling strategy that pools the available micro and macro-level data to produce a mutually consistent model of the trend and cyclical components of participation.

We find a significant procyclical pattern to participation in the available time-series data. However, we also identify some distinct trend influences on the participation rate, using longitudinal microdata. Together, these factors help to explain some of the movements seen in overall participation over the 1990s.

Our approach also allows us to construct forecasts for the participation rate, which would be a useful input into the sort of macroeconometric models used by policymakers. We assess our approach by conducting out-of-sample forecasts and find that it outperforms some conventional macroeconometric forecasts.

1 Introduction

The policymaker will frequently be interested in how 'tight' the labour market is currently and how tight it can be expected to be in the future. This assessment will in turn depend upon a view of how the demand for labour compares with its availability. In a tight labour market, where the demand for labour relative to its availability is high, wages might be expected to rise faster than otherwise. This in turn could lead to inflationary pressure in the goods market. For a monetary policy maker concerned with developments in inflation, a view on current and prospective labour availability is therefore an important part of its overall economic assessment.

In many of the standard macroeconometric models used by policymakers the wage is the outcome of a bargain between firms and (possibly unionised) workers. In these frameworks the bargaining power of workers is an inverse function of labour availability; the less labour is available, the more workers will have the power to demand higher wages. Typically these models use some measure of the unemployment rate as their gauge of availability. When policymakers use models of this sort for forecasting, they consequently often focus on what is happening to unemployment rather than on any other potential measures of labour availability.

Those people who are either employed or report themselves as unemployed are described as 'participating in the labour market'. But alongside this group is another group of non-participants, or people who are 'inactive'. For example, according to the Labour Force Survey (LFS), around 9 million of the working-age population were without employment in 2002, but only 1.5 million of these were unemployed according to the ILO definition of people being without a job who have actively sought work in the last four weeks and are available to start work in the next two weeks. The other 7.5 million were classed as inactive, or not participating in the labour market. If some portion of those who are inactive have the *potential* to be drawn into labour market activity, then looking at the unemployment rate might not be a sufficient statistic for gauging the overall availability of labour.

The size and nature of the pool of inactive participants in the labour markets suggests that they may indeed potentially be a significant source of labour availability. Jones, Joyce and Thomas (2003) point out that the inactive population is diverse, including students, the short and long-term sick and people looking after other family members. They present evidence that, although the likelihood that people flow from inactivity as a whole into employment is lower than for unemployment, the probability of flowing into employment from certain categories of inactivity is fairly high.

The potential importance of the inactive makes their decision of whether or not to participate in the labour market an important one. We can define the participation rate as the share of the population who are participating in the labour market at any point in time. For the policymaker, an assessment of current and prospective developments in this rate will help inform an overall view of labour availability, which may then have implications for inflation or other variables of interest.

In considering movements in the participation rate it is important to distinguish between movements due to cyclical factors from those affecting its trend. If a given change in the participation rate reflected a shift in some trend influence, then this change may be expected to endure and, other things being equal, have a larger effect on wage pressure than if it was driven by business cycle factors.

Chart 1 plots the UK participation rate for the period over which reliable data can be drawn. Over the 1980s the participation rate rose fairly steadily, reaching a peak in the early 1990s. It then fell back until the middle of the decade, when it began to rise again, but at a much slower rate than it had in the 1980s. Some of these movements in the UK participation rate are likely to reflect cyclical factors: the rise and falls in UK participation occur at roughly the same time as the periods of faster and slower UK output growth. But it is also likely that there were subtler trend influences on the overall aggregate participation rate over the period.

Previous studies in the literature have indeed found that the participation rate tends to be procyclical. Clark and Summers (1979) find the participation rate to be procyclical in US data. Similarly, Briscoe and Wilson (1992) and Cutler and Turnbull (2001) find UK participation rates to be procyclical across a range of age cohorts.

Underlying any changes in the overall participation rate in any period will be movements of people between inactivity and activity in both directions. Chart 2 shows the quarterly flows into and out of activity since 1993. As is evident, these flows are large: every quarter around 0.8 million people decide either to participate in the labour market or withdraw from participation. There is also some tendency for the gross flows to move together over the period, so that the *net* change in labour market participation in any quarter is much less than the flows in either direction.

The data on the gross flows into and out of activity are derived from the detailed micro-level individual survey responses to the LFS. However, these data are only available since 1992. It is as a result difficult to identify with certainty the cyclical response of the flows, as these data do not span a full cycle. Bell and Smith (2002) present evidence that the probabilities of moving from inactivity to employment and from unemployment to inactivity are both procyclical, while the probabilities of moving from employment to inactivity and from inactivity to unemployment are countercyclical. It should be noted that for the overall aggregate participation rate to be procyclical does not require that both the underlying gross flows are procyclical.

Alongside those influences arising from the business cycle, aggregate labour force participation is subject to numerous longer-term ‘trend’ influences. The most obvious of these in the UK data is the distinct patterns of male and female participation: the male participation rate has trended downwards over the past 20 years while, in contrast, the female rate has trended upwards over the period. Juhn, Murphy and Topel (2002) note that these trend influences are quantitatively significant (at least in the United States) and can be very important in the interpretation of the unemployment rate.

Gregg and Wadsworth (1999) have highlighted the fact that the downward trend in male participation has been accompanied by a rise in the numbers of men reporting long-term sickness and disability as their reasons for inactivity. Bell and Smith (2004) present evidence that the relative generosity of the benefits system in the early part of the period encouraged male workers to exit the labour market and declare themselves inactive. Besides any similar incentive effects from the welfare system, factors affecting female participation include declines in the numbers reporting they have family commitments that lead them to be inactive and changes in employer’s legal obligations in respect of employees wishing to return to work after childbirth. The rise in female participation has been accompanied by increasing skills and a rise in those forms of employment favourable to females, such as part-time and temporary work.

Alongside the distinct gender trends in participation, there have been trends along other dimensions. For example, among the 16-24 age group there has been a downward trend in the participation rate, while it has risen among the 25-34 age group. There have also been trends in participation with regard to education, with rises in inactivity among those with the lowest educational attainment (Jones, Joyce and Thomas (2003)).

Accompanying the literature that focuses on some of the broad trends in participation, is a large literature on modelling labour supply at the micro level. In the main it exploits the micro-level survey data using econometric techniques in order to determine the principal factors driving the labour supply decision, and estimates the elasticities of labour supply in response to shocks to these determining factors. These studies then provide a benchmark for policy analysis. For example, Blundell *et al* (1988) have looked at the sequence of tax reforms in the United Kingdom over the 1980s to examine their effects on female labour supply, while Eissa (1996) looks at the impact of tax reforms in the United States. Another branch of the labour supply literature looks at the effect welfare programs have on the decision to participate. Keane and Moffit (1995) model jointly the decision to work with the decision to participate in two US welfare programs. The micro-level studies highlight the need for any modelling approach to be robust to changing welfare regimes and other institutional factors. However, these studies do not in the main consider in detail any business cycle factors that may also affect labour supply decisions.

The limited availability of a long time-series of micro-level data makes a comprehensive account of the cyclical and trend influences on UK labour force participation difficult. The purpose of this paper is to develop a modelling strategy that pools the available micro and macro-level data to produce a mutually consistent model of the trend and cyclical components of participation. The model then allows us accurately to gauge the extent of business cycle influences on labour market participation alongside long-term trend influences.

Our modelling approach combines two strands. First, we identify the response of the participation rate to the business cycle using the long time-series of data on aggregate participation that is available. Our approach is similar to Cutler and Turnbull (2001) and Briscoe and Wilson (1992). Cutler and Turnbull estimate equations that incorporate a cyclical effect on participation by the inclusion of a simple output gap term. Briscoe and Wilson estimate similar equations, finding that output, the real wage, the share of manufacturing in output and the proportion of women with children are all important explanations of movements in participation. However, unlike these studies, our approach uses a state-space technique that treats the trend in participation as an unobservable variable. This avoids having to fit arbitrary functional forms to the trend and so may result in a better identification of the effect of the cycle.

The second strand to our approach follows the micro-based literature on labour supply, in using the individual supply responses from the detailed LFS data sets available post-1992 to model the decision of whether to participate in the labour market. The information set for these estimates includes detailed information on the characteristics of individuals, such as educational attainment, age, as well as reasons cited for activity/inactivity. These factors potentially explain a substantial fraction of the trend in participation. However, as discussed, the short time-series for the microdata makes it difficult to identify a business cycle effect on the participation rate. One of the innovations in this paper is that we impose the business cycle effect we have identified from the longer time-series data in the first strand of our approach, thereby producing a consistent model that can account for both the cyclical and trend influences on participation.

The policymaker will often require a forecast for future labour market participation. This will assist in forecasting the availability of labour relative to its demand, which in turn will have implications for forecasts of future wage and price pressures. Standard approaches to forecasting the participation rate, such as the Cutler and Turnbull approach[(1)] often combine some simple detrending techniques with a measure of the business cycle to produce forecasts. Alternatively, simple

(1) The Cutler-Turnbull approach to forecasting participation was incorporated into the Bank of England's Macroeconomic Model for a period of time.

rules-of-thumb or extrapolation of recent outturns may be used.

One consequence of our combined model is that we are able to generate forecasts for the participation rate that embody a consistent cyclical response with a sophisticated micro-level forecast of the trend. These forecasts are of a kind that could be incorporated into macroeconometric models. By exploiting the richness of the LFS microdata, our model offers a potential improvement in forecast accuracy, as well as the ability to explain at a deeper level what is driving the trend over any forecast. We test the forecast performance of our combined model by constructing out-of-sample forecast tests, showing that it outperforms some other commonly used approaches.

The rest of this paper outlines the aggregate and micro models we apply to the problem of modelling participation, and how forecasts could be generated from either approach. It then describes how the two approaches are combined to produce a consistent model of trend and cycle, and how this in turn can be used for forecasting. We then discuss our estimation results and the implications they have for thinking about developments in the participation rate. Finally, we assess our approach by constructing out-of-sample forecast tests. We also suggest that the combination of macro and micro models is an approach that could be applied more widely in forecasting macroeconomic data.

2 Modelling the participation rate

In this paper we are interested in modelling the aggregate UK participation rate. This will often be the ultimate variable of interest as it will help inform the assessment of potential labour supply at any point in time. Also, from a forecasting perspective, it will help inform a view of future labour market developments.

We distinguish between two broad approaches to building a model of aggregate participation, before suggesting a third that combines these two consistently.

i) An aggregate approach

Aggregate data on the UK participation rate are available annually from 1984 and quarterly from 1992. One common approach to modelling data of this sort is to identify a set of trend and cyclical factors. Traditional approaches to the problem of separating trend and cycle in macroeconomic time series often involve some mechanical detrending of the data. One popular approach is to apply the 'Hodrick-Prescott' (HP) filter to the data in question. However, one of the drawbacks to using such a method on data where one suspects there is a discernible cyclical influence is that the trend and cycle are not jointly estimated. Indeed, the HP filter can only be rationalised as the unrestricted optimal trend estimator of a series when the non-trend influences on the series are white noise (Harvey and Jaeger (1993)). A further drawback to the HP filter, or simpler moving averages of the data, is that spurious cycles can be induced into any detrended series.

An alternative approach to detrending a time series follows the 'structural time-series' approach popularised by Harvey. These structural time-series models are set out explicitly in terms of observed and unobserved components that have a direct interpretation. For example, the appropriate model for participation might be set out as:

$$A_t = \gamma_t + \psi_t + \varepsilon_t \qquad \varepsilon_t \sim NID(0, \sigma^2_\varepsilon) \qquad \textbf{(1)}$$

where A_t is the observed series, γ_t is the trend, ψ_t is the cycle and ε_t is a white noise error. The trend can then be modelled as a random walk:

$$\gamma_t = \gamma_{t-1} + \varsigma_t \qquad \varsigma_t \sim NID(0, \sigma^2_\varsigma) \qquad \textbf{(2)}$$

where ς_t is also a white noise error.

Alternative formulations of the trend are also possible within the structural time-series approach.

The structural time-series approach as set out above has a number of advantages over simpler forms of detrending. Unlike the HP filter method, it estimates the trend and cycle in the observed series simultaneously. This should avoid the possibility of inducing spurious cycles into a detrended series and/or arriving at the wrong conclusion on the size of cyclicality in a series. Further, by allowing for the underlying trend to be modelled stochastically, the structural time-series approach should not confuse the persistence of shocks to the *observed* series with shocks to the *unobserved* trend. So, for example, short-term shocks to observed participation may be short-lived, but shocks to the trend in participation automatically display high levels of persistence, consistent with the slow movement of demographic trends and other longer-term movements.

Our approach to separating the trend and cyclical influences on aggregate UK participation broadly follows the structural timeseries approach, explicitly treating the trend influences on participation as an unobserved stochastic process.

There is a fairly clear relationship between the UK participation rate and cyclical movements in output (Chart 1). It is *a priori* desirable that our model captures these endogenous elements to participation movements, so that feedbacks between growth and participation can be fully accounted for. In essence, we need to replace the cyclical term ψ_t in equation **(1)** with some measure of the business cycle.

Bearing the preceding discussion in mind, we model the observed aggregate UK participation rate as a function of an unobserved trend term (which is clearly driven by many diverse influences at the micro level) and some measure of the economic cycle. Allowance is also made for gradual adjustment in the participation rate by allowing the previous period's participation outcomes to influence the current value:

$$A_t = \alpha A_{t-1} + \gamma_t + \beta\varphi_t + \varepsilon_t \qquad \textbf{(3)}$$

where A_t is the participation rate, γ_t is the trend in participation[2] and φ_t is a measure of the business cycle.

It is of course quite possible that the different subcomponents of those who do or do not participate have distinct cyclical responses. For example, students may not respond to cyclical variation in the same way as those who are long-term sick. However, we are interested here in modelling the overall aggregate participation rate. Also, when we combine the aggregate and micromodels as set out below, we allow for a wide variety of controls to influence the decision to participate, and even allow

[2] The long-run trend is $\gamma_t/(1-\alpha)$.

these estimates to vary over time. Nevertheless, as a longer span of consistent data becomes available, it may be possible to explore richer cyclical structures.

The unobserved stochastic trend process, γ_t, is modelled as a simple random walk:

$$\gamma_t = \gamma_{t-1} + \varsigma_t \qquad \textbf{(4)}$$

In principle one could also allow for a drift term in **(4)**. But there is no strong intuitive reason for specifying a permanent drift in labour force participation and, in any case, the presence of a drift term was rejected in the final specification.

The errors in **(3)** and **(4)** are assumed to be iid with variance σ^2_ε and σ^2_ς and cov($\varepsilon_t, \varsigma_t$)=0 respectively. We therefore rule out the possibility of co-varying shocks across the observed and unobserved components.

The parameters in this model can be estimated using techniques that are now common in time-series work on unobserved components. The Kalman filter algorithm provides optimally updated estimates of the unobserved trend in participation, γ_t, given a set of starting values for the trend and the other parameters in the model. The likelihood function of the model can then be constructed, assuming that the error terms ε_t and ς_t are normally distributed. Maximising this likelihood through standard techniques generates estimates of the parameters in **(3)** and **(4)**. This joint estimation procedure ensures that the estimates of trend participation and the cyclical influence are the 'best' in explaining movements in UK aggregate participation given the data currently available.

It is common in these models to impose a restriction on the ratio of the error variances in **(3)** and **(4)** such that $\sigma^2_\varsigma / \sigma^2_\varepsilon < 1$. This in effect ensures that trend participation is smoother than observed participation, while still allowing γ_t to follow a stochastic process. Setting this restriction is somewhat arbitrary, as there is little guidance one can look to in judging how smooth the trend should be. In the estimates reported in Section 3, we set this ratio at 0.1. By implication the standard deviation of the trend is therefore by assumption around a third of the standard deviation of observed participation. We also report in Section 3 the sensitivity of the trend to variations in this restriction.

If we wanted to use this model to forecast, it would involve iterating on equations **(3)** and **(4)**. Equation **(3)** indicates that the optimal forecast for the trend in participation at time $T+i$ (γ_{T+i}) will be equal to the value of the trend at the start of the forecast (γ_T). This follows from the random walk assumption. The forecast for actual participation also requires a projection for the cyclical term φ_t. This will be a common output in most macroeconomic forecasts.

ii) A micro approach

From the labour economist's perspective, participation is an individual choice that can vary substantially according to the individual's characteristics and circumstances. At the micro level the participation rate is a product of the underlying flows to and from activity, so the micromodel begins with these decisions.(3) The UK Labour Force Survey (LFS) provides detailed information on the individuals who flow to and from activity in any seasonal(4) quarter after Spring 1992.(5) Alongside demographic variables, there is information on education, the willingness to work and the reasons cited for inactivity. In addition to the likely importance of these cross-sectional influences, the state of the business cycle is also likely to be a key influence in individuals' decisions.

In principle, exploiting this rich data set provides an alternative 'structural' approach to modelling the participation rate, that could in turn be used to produce a 'bottom-up' forecast for aggregate participation movements. Aggregating over individuals yields a formula for the working-age participation (or activity) rate, A_t^{wa}, that includes the

(3) Another way of viewing the decision would be to consider the flows between unemployment, employment and inactivity separately. Our current approach does allow for substantial mean differences in transition rates according to employment status, but does not allow for any interaction with demographics for example. We do not pursue this in this paper as it would greatly increase the econometric complications in estimating the complete transition matrix.
(4) The seasonal quarters are December-February (winter), March-May (spring), June-August (summer) and September-November (autumn).
(5) The LFS panel data only matches individuals who stay at the same address between quarters. If household and job mobility are positively correlated (as is likely) the LFS may underestimate job mobility.

realised levels of active and inactive individuals and how many will change their status during the quarter:

$$A_t^{wa} = \left(1 - \Pr(a \to i | \mathbf{X_{ai}})\right) A_{t-1}^{wa} + \Pr(i \to a | \mathbf{X_{ia}})(1 - A_{t-1}^{wa}) + \varepsilon_t \qquad \textbf{(5)}$$

where $\Pr(a \to i | \mathbf{X_{ai}})$ represents the probability of an individual, *i,* moving from activity into inactivity. This probability will depend upon a vector, $\mathbf{X_{ai}}$, of information relevant to the individuals' participation decision. Similarly, $\Pr(i \to a | \mathbf{X_{ia}})$ represents the probability of an individual moving from inactivity to activity.

The elements of equation **(5)** can be estimated using standard techniques for probability models on individual-level data. Here, we model the probabilities for the underlying flows as linear probability models, which simplifies the algebra considerably and should approximate typical decisions well:

$$\Pr(a \to i | \mathbf{X_{ai}}) = \mathbf{X_{ai}} \boldsymbol{\beta}_{\mathbf{ai}} \qquad \textbf{(6)}$$

$$\Pr(i \to a | \mathbf{X_{ia}}) = \mathbf{X_{ia}} \boldsymbol{\beta}_{\mathbf{ia}} \qquad \textbf{(7)}$$

In principle more sophisticated probit or logit models could also be used. But imposing our cyclical restrictions on these models would be computationally difficult (being non-linear and requiring numerical evaluation). In any case, because the estimates are typically substantially different from probability one or zero, using linear techniques will not result in significantly different results.

One of the key determinants of these probabilities will be the agent's view on the state of the labour market or business cycle. One element in $X_{\mathbf{ai}}$ and $X_{\mathbf{ia}}$ will therefore be a cyclical variable, X_{cyc}. But at the level of the individual a wide variety of other factors are also relevant to their participation decision ($\mathbf{X}_{\mathbf{ai},ncyc}, \mathbf{X}_{\mathbf{ia},ncyc}$). These factors are essentially anything that might influence the value of the individual's inactive opportunities, which would logically include the individual's age, education, their family situation and their health status.

We can directly account for movements reflecting the business cycle in the model by separating the trend influences from the cyclical element. Equations **(6)** and **(7)** are general enough to include a variable (X_{cyc}) to account for this cyclical response, which could be included independently in each model of probability:

$$\Pr(a \to i|\mathbf{X_{ai}}) = \mathbf{X_{ai}}\boldsymbol{\beta}_{\mathbf{ai}} = \mathbf{X}_{\mathbf{ai},ncyc}\boldsymbol{\beta}_{\mathbf{ai},ncyc} + X_{cyc}\beta_{ai,cyc} \qquad \textbf{(6')}$$

$$\Pr(i \to a|\mathbf{X_{ia}}) = \mathbf{X_{ia}}\boldsymbol{\beta}_{\mathbf{ia}} = \mathbf{X}_{ia,ncyc}\boldsymbol{\beta}_{ia,ncyc} + X_{cyc}\beta_{ia,cyc} \qquad \textbf{(7')}$$

If X_{cyc} is an appropriate measure of the business cycle then $X_{cyc}\hat{\beta}_{ai,cyc}$ will account for the average business cycle response during the sample period, leaving $\mathbf{X}_{\mathbf{ai},ncyc}\hat{\boldsymbol{\beta}}_{\mathbf{ai},ncyc}$ orthogonal to the business cycle in an OLS estimate. The same approach works for flows from inactivity to activity.

Once the micromodel has been estimated, a forecast for the aggregate participation rate can be constructed by using equations **(5)** to **(7)** to generate forecasts for the flows into and out of activity over the forecast period in question. This will require projections for the underlying characteristics $\mathbf{X_{ai}}$ and $\mathbf{X_{ia}}$. Some of these explanatory variables are demographic terms, which are fairly easy to forecast as they move relatively slowly and could be treated as constant over a forecast period. Other variables, such as the reasons cited for inactivity, are less predictable and may be related to the business cycle in an unknown way.

iii) A combined approach

One of the strengths of the micromodel is that it provides an explicit modelling of the underlying trend influences on participation. But the lack of a long time-series of microdata makes identifying the cyclical component to participation difficult in this model. A third approach therefore suggests itself, which combines the cyclical identification from the aggregate data with the modelling of the trend at a micro level. There is an implicit correspondence between the aggregate model set out in equations **(3)** and **(4)** and the micromodel. This is evident by substituting equations **(6')** and **(7')** into **(5)**:

$$A_t^{wa} = \left(1 - \mathbf{X}_{\mathbf{ai},ncyc}\boldsymbol{\beta}_{\mathbf{ai},ncyc} - \mathbf{X}_{\mathbf{ia},ncyc}\boldsymbol{\beta}_{\mathbf{ia},ncyc}\right)A_{t-1}^{wa} + X_{cyc}(-A_{t-1}^{wa}\beta_{ai,cyc} + (1 - A_{t-1}^{wa})\beta_{ia,cyc}) + \mathbf{X}_{\mathbf{ia},ncyc}\boldsymbol{\beta}_{\mathbf{ia},ncyc} + \varepsilon_t \qquad \textbf{(8)}$$

The formula in **(8)** involves a lagged dependent variable, a cyclical term, and a trend term - a similar formulation to the model for aggregate data. This equation could not be estimated via a time-series regression without further restrictions, because all of the coefficients are time varying, but it does underline that a trend component derived from a model of the flows is potentially consistent with our earlier state-space specification.

The cyclical response of the aggregate (working-age) participation rate, A_t^{wa}, in the micromodel is found by taking the derivative of **(8)** with respect to the variable X_{cyc}:

$$\partial A_t \big/ \partial X_{cycle} = -\hat{\beta}_{ai,cycle} \cdot A_{t-1} + \hat{\beta}_{ia,cycle} \cdot (1 - A_{t-1}) \qquad \textbf{(9)}$$

If the cyclical response in **(9)** were well identified, we should find it to be broadly similar to that estimated from the aggregate data model. But the short sample length and the lack of a complete cycle in the data mean that the cyclical response is poorly identified. However, we can achieve consistency by constraining the microcoefficients such that the implicit cyclical response in **(9)** is the same as that estimated from the aggregate model. The imposition of the cyclical response means that the endogenous response of participation to the economic cycle should now be correctly accounted for in the micromodel.(6)

It is worth noting that the constraint on the cyclical response in the micromodel need not imply procyclicality in both of the underlying flow equations. The aggregate

(6) As well as the inherent identification problem, there may be other reasons why we might expect the effects of the cycle to differ before and after 1992. For example, various labour market reform measures may have changed the cyclical responses of hiring and firing. In order to explore these possibilities we have experimented with a joint structure, in which our cyclical variable is also estimated using Kalman filter techniques. However we find little difference in these results to our simpler approach. As our model is in part intended as a tool for forecasting aggregate participation we believe the benefits from our approach outweigh any gains from complicating the method.

response will be procyclical when $\hat{\beta}_{ai,cycle} \cdot A_{t-1} < \hat{\beta}_{ia,cycle} \cdot (1 - A_{t-1})$, which could easily hold while both flows are countercyclical. Rather, the constraint is a cross-equation restriction on the cyclical response across the flow equations. We imposed this in the estimation by solving for the minimum adjustment to both coefficients that sets the derivative in **(9)** equal to the cyclical response from the time-series estimate.

A consistent forecast for aggregate participation, conditioned on a projection for the output gap variable and on a profile for the underlying trend movement in participation over the period in question, can now be generated using equations **(3)** and **(8)**. Both of the 'right-hand side' inputs are available in our approach: a forecast of the output gap will be one of the key products of many macroeconometric projections, while the constrained micro estimates will allow for a forecast of the trend in participation to be produced.[7]

3 Estimation

i) Aggregate model estimates

We estimated the aggregate model set out in Section 2 using the available LFS data on aggregate participation. Since the data are only annual between 1984 and 1992, we interpolate the data to generate a quarterly series for this period. The interpolation procedure makes use of the quarterly variation in other available sources while constraining the data to meet the annual LFS totals. For employment, the available data are ONS data on Workforce Jobs, while for unemployment it is the Claimant Count. Quarterly inactivity data are then derived as the difference between these series and a smoothly interpolated estimate of population. Our interpolation procedure reflects the best quarterly variation that can be estimated from available sources.

[7] One problem in implementing the micromodel is that it is (unavoidably) estimated on data covering the population of working age. But we are interested in the participation rate covering the population aged 16 and over. In using the model to derive a forecast for the trend we include the non-working age groups according to the following formula, which essentially assumes the activity rate of the non-working age is fixed over the forecast horizon.

$$A_t = \left(1 - p_t^{nwa}\right)\left(\mathbf{X_{ai}}\boldsymbol{\beta}_{\mathbf{ai}}\, A_{t-1}^{wa} + \mathbf{X_{ia}}\boldsymbol{\beta}_{\mathbf{ia}}\,(1 - A_{t-1}^{wa})\right) + p_{t-1}^{nwa} * A_{t-1}^{nwa} + \phi_t + \varepsilon_t \qquad \textbf{(10)}$$

where p_t^{nwa} is the non-working age fraction of the 16+ population and A_{t-1}^{nwa} is the activity rate of the non-working age. Equation **(10)** can then be iterated forward to produce forecasts for the non-cyclical trend component in participation, conditioned on a profile for the explanatory variables.

Given that we are using the data to estimate a cyclical effect with a significantly lower frequency than one quarter, our estimates will not be greatly affected by exact choice of interpolation procedure. As a check, we have estimated the model with some variations in the exact interpolation approach, finding little difference in the identified cyclical effect. We have also estimated our model on annual data over the full sample 1984-2002, again with very similar results.

Ideally we would want to use an even longer time series of aggregate data to capture the average cyclical response of participation. However we are restricted in doing so by two factors. First, the annual LFS only started in 1984. Before this, the survey was biannual and we do not believe it can be adequately interpolated to give a reasonable quarterly profile. Second, the definition of unemployment used in the LFS changed at the start 1984 to bring it into line with ILO categorisations. The effect of this change seems to be to generate a large 'spike' in the participation data around that time. Since this spike is not related to cyclical or trend factors, including data before it tends to be problematic in estimation. So we decided to use only data after 1984. However, this is still almost 20 years of data, covering a number of changes in the pace of growth as well as several recessions and 'booms', and so should be sufficient to identify the cyclical effect with reasonable accuracy.

An important variable choice for our estimation of the aggregate model is the measure of the business cycle. We tested a range of possible candidates in estimation. Among these were GDP and consumption, detrended by simple linear time trends and HP filters, as well as a measure of capacity utilisation with employment in total hours as the labour input variable. In principle a measure of potential supply derived from a production function may be the most appropriate measure of the business cycle variable. But the problem here is that this measure would itself depend upon an estimate of trend participation and this would therefore require its simultaneous estimation within our participation framework. We take the simpler estimate to isolate modelling the participation trend from estimates of the business cycle and note that a conceptually better estimator might be possible.

We estimated equations of the form **(3)** and **(4)**, testing down for lags of detrended GDP and participation. Of the business cycle influences on participation estimated

(Table A), a simple measure of GDP detrended by a linear time trend worked as well as the alternatives when assessed by the Akaike Information Criterion (AIC). This is not particularly surprising, as the detrended GDP measure displays a clear cyclical variation and is unaffected by some of the uncertainties that can surround measures which use estimates of the capital stock. The selected specification contained one lagged dependent variable and the cyclical variable lagged one period.

The estimates reported in the first column of Table A give the coefficients for the simple participation model.[8] The coefficient on lagged participation, at 0.7, implies that the half-life of a shock to participation above trend will be around three quarters. Temporary shocks to participation above equilibrium will therefore be fairly quickly reversed in this specification, which is a desirable property given the fairly erratic nature of the quarterly participation rate. The cyclical response in the estimated models implies that a 1% increase in GDP above 'trend' results in the participation rate increasing by around 0.15% after two years.

Chart 3 illustrates the cyclical component of participation estimated from our model together with our measure of the business cycle. The estimates display a plausible procyclical pattern. Much of the rise in participation between 1988 and 1990 is attributed to the influence of the business cycle. Likewise, much of the rise in observed participation since 1997 is also put down to cyclical influences. Chart 4 illustrates the sensitivity of the trend to differing restrictions on the ratio of the variance in the state and measurement equations. As can be seen, differences in the restriction have comparatively little impact on the backed-out trend.

ii) Micromodel estimates

Our micro estimates essentially require estimation of the two underlying flow equations.

---

[8] One difficulty in estimation is that quarterly LFS data are only available after 1992. We use interpolated data for the period 1984-92 in our estimates. As a cross-check on our estimates on this quarterly data, we also estimate equations following the same method using annual data. We find the long-run cyclical impact to be very similar to that implied by the estimates in Table A.

Table B shows the coefficients from a model that estimates the probability of moving into activity over the sample 1994 Q1 to 2001 Q2. The first column of estimates are unconstrained: there is no restriction on the coefficient of the cyclical variable. The decision to participate depends upon the value of an individual's 'inactive' options relative to their expectations for the labour market. Age, sex, and education were all found to be significant factors in the probability that an individual will become active in the labour market.

The age controls included yield a smooth flexible profile by age, augmented with specific responses for key groups, in particular school age and young women.(9) It is important to capture these demographic variables in our estimates, as although they should move reasonably slowly in a large population like the inactive, either gradual changes in the frequency or the response of these groups can contribute significantly to an underlying trend in aggregate participation.

The other major category included in the model is the reason that individuals cite for their inactivity and their expressed interest in finding work. These variables are highly significant and could reveal either long-term trends or responses to labour market conditions. The student variables stand out as particularly substantial and statistically significant, which is interesting given attempts by UK governments to increase participation in further and higher education. Similarly, all of the long-term sickness variables are significant. The increased rates of male inactivity related to reported long-term sickness has been widely noted elsewhere as a phenomenon in the United Kingdom.(10)

The second set of estimates model the probability of moving from activity to inactivity. The first column of Table C shows unconstrained estimates for this process. Demographic variables are again statistically significant in these estimates. In addition it appears that some forms of employment, such as family and government employment, are more likely to lead to inactivity. Some durations of unemployment are also more likely to lead to a movement into inactivity.

(9) We experimented with adding trend terms for some of these groups on the basis of changing coefficients over the full sample, but only the participation of ages 16 and 17 was significantly trended.
(10) See Gregg and Wadsworth (1999) and Bell and Smith (2004).

iii) *Combined model*

For the combined model, we impose the cyclical response on the micromodel from that estimated in the time-series model with detrended GDP as set out in Section 2(iii). The second columns in Tables B and C give the results for the flows into and out of activity.

It is clear that neither equation rejects the imposed cyclical constraint,[(11)] although this is not surprising as, consistent with the arguments above, the micromodel is unable to identify the correct level of the cyclical variable according to the standard errors reported. Indeed, both sets of estimates generally have very similar coefficient values for the other explanatory variables and also similar root-mean-square errors when constrained by the cyclical effect. This should not be interpreted as suggesting that the combined model adds little incremental value. Rather, it confirms that the micromodel is fundamentally unable to estimate a cyclical component on its own.

The second column of Table B shows the coefficients from the constrained model for the flow out of inactivity and into activity. We continue to find age to be a significant factor in determining whether or not someone decides to participate in the labour market. Gender is also found to be highly significant: females are found to have a greater likelihood of transitioning. This is not surprising given that the stock of female inactivity is likely to contain a relatively high proportion of people who have chosen to be out of the labour market for temporary reasons.

The most significant other factor in determining the tendency to choose to participate under the constrained model is whether or not someone is a student, for obvious reasons. More generally, we find that education continues to be an important factor in the probability that an individual will become active in the labour market, with the more skilled more likely to flow into activity.

The reasons cited for inactivity and the expression of interest in work also remain important explanatory factors in the constrained model. In particular, those inactive

[(11)] The reported standard errors are adjusted for clustering, which has the effect of increasing the already fairly large standard error on the cyclical variable.

who describe themselves as long-term sick are much less likely to flow into activity the following quarter.

The second column in Table C shows the constrained estimates for the probability of moving from activity to inactivity. We find that gender is again important: females are more likely to flow into inactivity from activity than males. The most important of the other categories in determining the likelihood of flowing into inactivity is the nature of the activity that the individual is currently doing. In particular, being in family employment or being unemployed, rather than being in regular employment, makes someone considerably more likely to choose not to participate in the labour market in the following quarter.

To summarise the findings from our combined model, then, we find many of the factors that have been highlighted elsewhere[(12)] to be important in determining the recent trends in participation. And we have modelled these factors in a way that consistently accounts for business cycle influences, so we can be confident that they are important.

As highlighted in the introduction, an important requirement of any model of the participation decision is an ability to deal with changes in the incentives to be active in the labour market, such as developments in the benefit regime or changing institutional characteristics more generally. One of the advantages of the combined model is that the size of the panel allows us to re-estimate the micro trend over moving 'windows' of data while still maintaining consistency with our cyclical identification. This should ensure that our estimates of the likelihood of moving between activity and inactivity are kept up-to-date.

Tables D and E present two examples from a rolling-window estimation over the period 1994 Q1-2001 Q2. Generally speaking, the estimated transitions appear fairly stable over this period. The importance of gender in determining the likelihood of flowing between activity and inactivity, or *vice versa*, declines somewhat in the second half of the sample. Those with higher education levels also show a relatively

[(12)] See for example, Gregg and Wadsworth (1999) and Jones, Joyce and Thomas (2003).

greater likelihood of flowing into activity in the second half of the sample, and a relatively lower likelihood of flowing into inactivity. But many of the changes are subtle; in particular, there appears to be no evidence that the likelihood of flowing into activity has increased for the sick.

4 Out-of-sample forecasts of participation

As we have discussed, one possible use of our model of participation is in forecasting. This also offers a good test of assessing its validity, as we can compare its out-of-sample forecast performance against some alternative approaches.

We use our estimated model to construct forecasts as set out in Section 2(iii). This involves using the constrained micromodel of the non-cyclical element of participation (equation **(10)**) to provide projections up to eight quarters ahead for the Kalman filtered trend extracted from the state-space formulation (equations **(3)** and **(4)**). A projection for output over the forecast period will then add the endogenous response of participation to the business cycle.

But before the combined model is used for forecasting in this way, an important question is whether the trend from the micromodel matches the trend derived from the Kalman filter. Chart 6 plots the one-step-ahead forecast from the micromodel against the Kalman filtered trend. The one-step-ahead forecast from the micromodel is the appropriate comparison because it parallels the random walk assumption of the state equation. As the chart shows, the two trends fit well, with the absolute mean divergence between the two being only 0.04 percentage points over the sample 1994 Q1-2001 Q2). This is a useful test because the only arithmetic requirement is that these two trends must match on average, as the cyclical response from the aggregate model is imposed on the micromodel so that the errors average zero in the two models over the estimation periods. But whether they match accurately *at all points in time* is ultimately an empirical question, and the fact that they do means that we can indeed use the micromodel to provide a consistent forecast of the trend generated from the Kalman filter.

The most appropriate way to assess our proposed model of aggregate participation is through out-of-sample forecast tests, which effectively attempt to replicate the errors that would be made in using our method in 'real time'.

This is the approach we follow. Starting in the first quarter of 1996, we re-estimate the models set out in equations **(3)** to **(7)** iteratively, moving forward a quarter at a time. The estimated coefficients therefore reflect only the data the forecaster would have had at the time. We then construct rolling forecasts for the participation rate for the next eight quarters from 1996 onwards. The only exception to this procedure is that we use final GDP data rather than real-time data or model forecasts in our output gap terms.

We compare the mean and variance of the forecast errors from our approach to a number of alternatives a forecaster may plausibly decide to use instead. The most obvious alternative for comparison is using *just* the information from the aggregate time-series model. The state equation in the aggregate approach assumes that the trend follows a random walk. So the participation forecast is a fixed value in this approach. Our comparison here is therefore essentially whether the micromodel can add useful information, and so do better than the random walk assumption. Our prior is that this is unlikely at short horizons, because the cyclical identification in the micromodel is itself implicitly based upon the random walk assumption. But at horizons further out, our intuition is that the forecasts from the micromodel may not simply hold participation fixed for all time. And Chart 5 indicates that this is the case. Successive forecasts for the trend in participation based on the micromodel are rarely flat across the forecast horizon, but exhibit perceptible trends.

Another suitable comparison for our combined approach is one based on using a HP filter. In this approach we assess the underlying trend in participation using a HP filter and then iteratively estimate equations similar to **(3)** based on this trend. We then use this equation for forecasting, extrapolating the filtered trend to participation on the basis of recent outturns.

Table F sets out the mean and standard errors of the out-of-sample forecast errors for the period 1996 Q1-2001 Q2 from our approach and for the two alternatives described above. The standard errors of the forecasts from our approach are indeed lower than for the two alternatives. These results hold at least out to a horizon of eight quarters, which would cover a period of interest to many policymakers. The improvement of the combined model over using just the aggregate model at longer horizons is also shown in Chart 7. The four quarters ahead forecast for participation based on the combined model can be seen to track the outturns better than the forecasts based on the simple Kalman filter approach.

The gain in forecast efficiency in the combined approach is not large compared with using just the Kalman filter model to forecast participation. But our proposed approach to modelling the participation rate also offers the additional advantage of being a more structural forecast of the trend. This will often be useful in understanding what is driving the underlying movement in the participation rate, and will help explain any errors that are made in the forecast. The forecasts of the trend are also likely to be robust to structural shifts in the underlying determinants, such as changes in the benefit regime, as periodic re-estimation should take on developments as they happen.

5 Conclusion

This paper has proposed an approach for modelling UK labour force participation that makes uses of the available micro and aggregate data to produce a mutually consistent model of the trend and cyclical components. We find that there is a significant cyclical component to the participation rate. Alongside this, there is also a range of influences that help explain the trend in participation. These trend influences reflect many of the factors noted elsewhere, such as gender, age, educational attainment and reported disability. But while other papers tend to focus on individual factors that have driven participation, we provide a model that comprehensively and consistently accounts for both the cyclical and diverse micro aspects of the decision to participate.

One of the potential uses of our model is in providing a forecasting method for the participation rate that may be incorporated into macroeconometric models. There are a range of potential alternative approaches, but against some fairly standard ones we have provided evidence that our approach does better.

Finally, we believe the approach we have taken in this paper may have wider applications. The econometrician is often faced with a reasonably long time series of data but much shorter panel information. In exploiting the two sources of information, our approach offers the chance for these data to be combined in a consistent manner, to deliver better analysis and forecasts.

Appendix

Chart 1: The UK participation rate and a measure of the business cycle

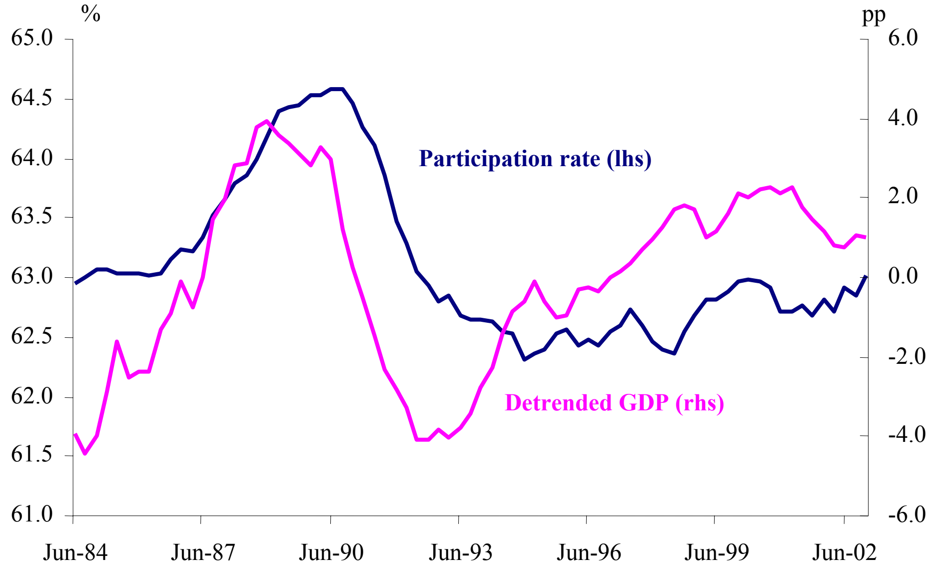

Chart 2: Flows into and out of activity

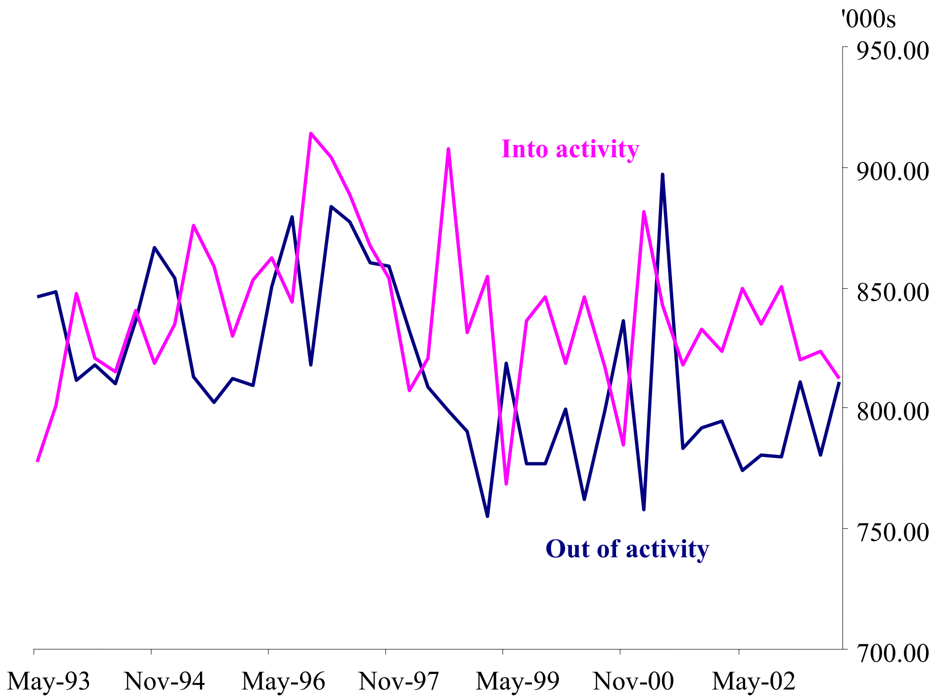

Chart 3: The cyclical component of participation estimated from the state-space formulation

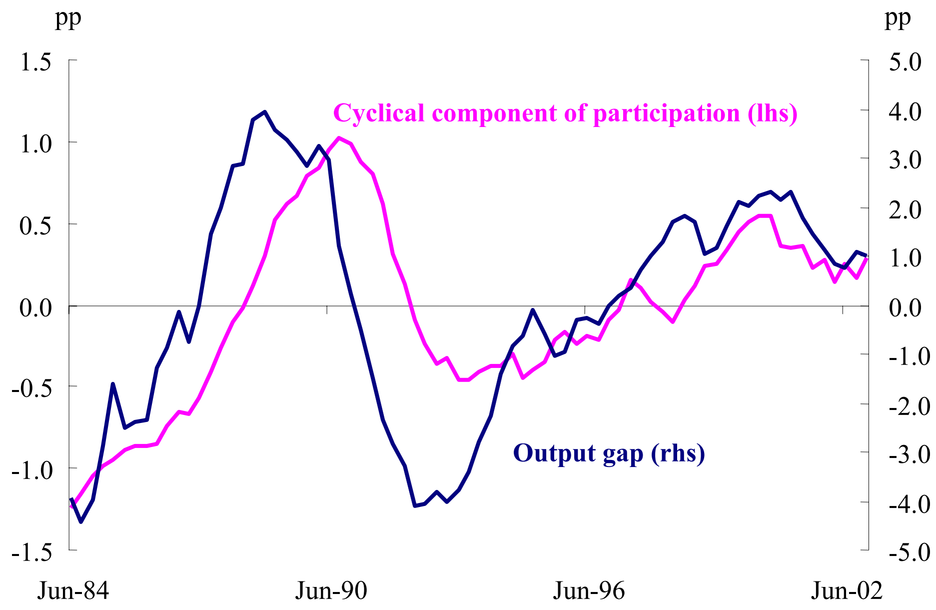

Chart 4: Trends in participation based on differing variance ratio restrictions

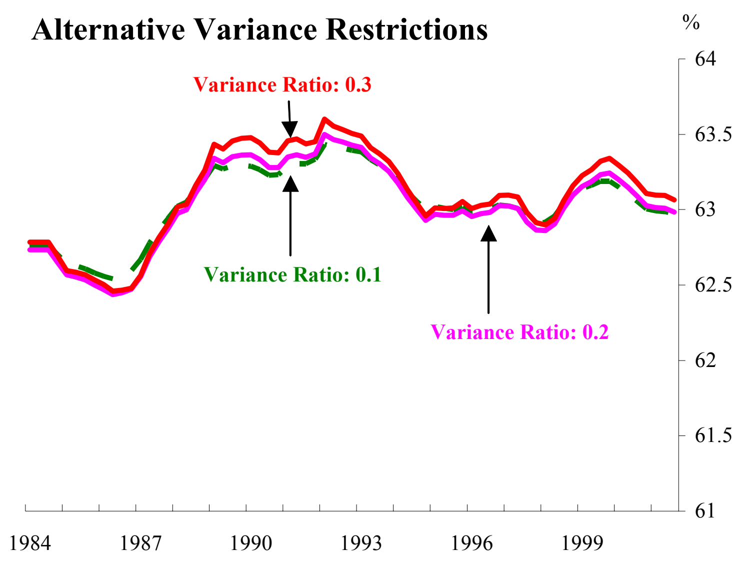

Chart 5: Successive forecasts for the trend in participation from the combined model

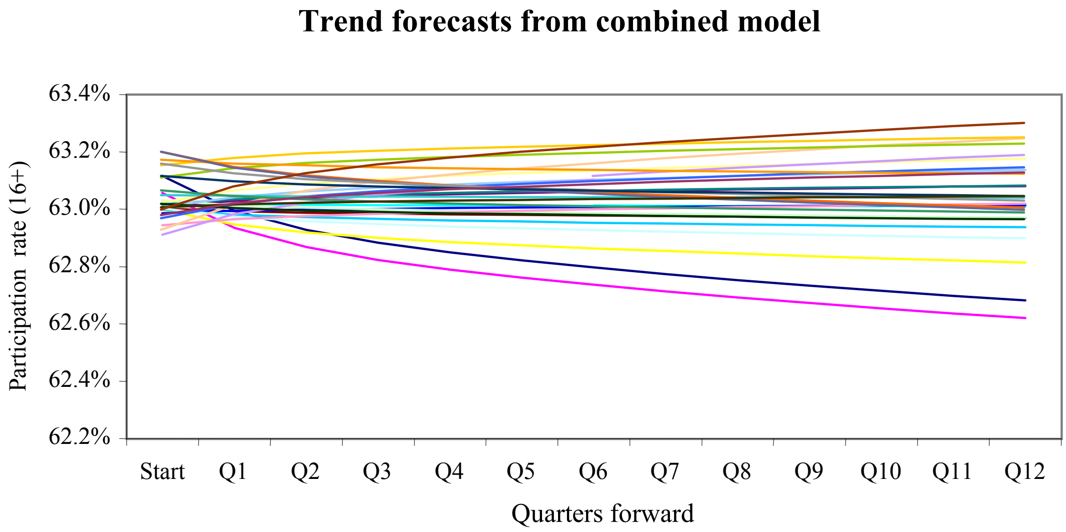

Chart 6: Comparing the trends from the aggregate and micromodels

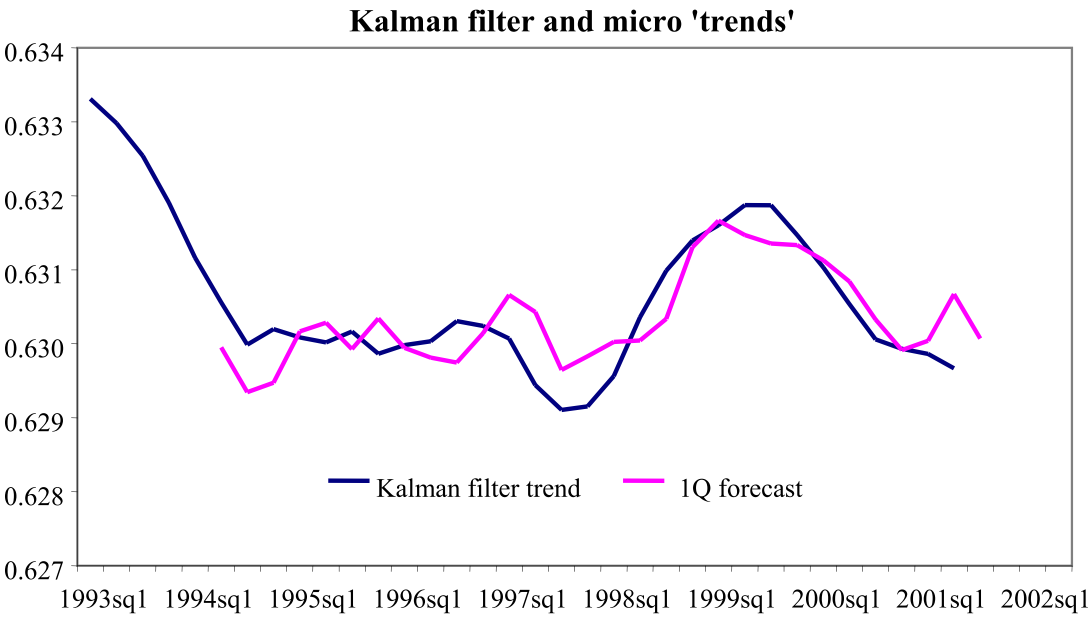

Chart 7: One and four quarter ahead forecasts from the aggregate and micro models

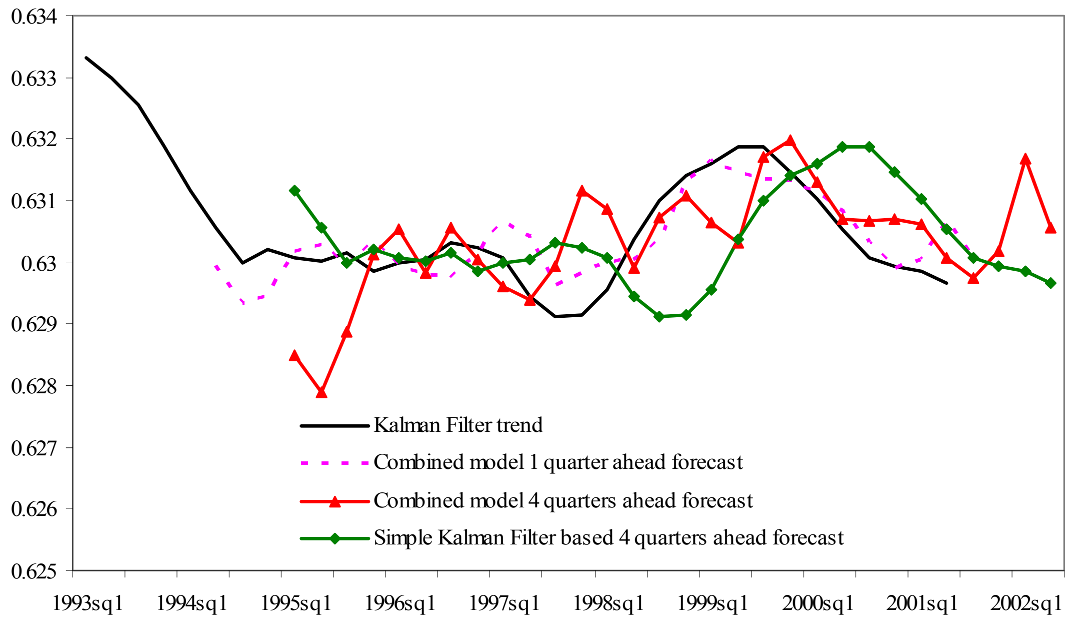

Table A: Estimates from state-space formulation of participation equation

	i	ii	iii	iv
	GDP	**GDP**	**Consumption**	**Capacity utilisation**
Detrending:	Linear	HP filter	Linear	
α	0.72	0.77	0.64	0.89
	(0.071)	(0.0596)	(0.0885)	(0.0456)
β	4.82	5.66	4.22	3.56
	(1.6)	(1.93)	(1.29)	(2.12)
Log-likelihood	33.5	32.9	34.54	30.82
AIC	-0.91	-0.87	-0.91	-0.81

(t-statistics in parenthesis).

Table B: Linear probability models of transition to active status

Variable	Unconstrained	Constrained
Detrended GDP	-20.58 ***	-8.71 (NA)
Higher Degree	2.49 ***	2.48 ***
Higher Vocational Training	1.22 ***	1.22 ***
A Level	0.05	0.05
Vocational Training	1.92 ***	1.89 ***
Apprenticeship	-0.20	-0.19
Lower Education	-2.16 ***	-2.15 ***
Age	-2.17 ***	-2.17 ***
Age^2/100	4.61 ***	4.60 ***
Age^3/1000	-0.36 ***	-0.36 ***
Female	19.87 ***	19.88 ***
Female*Age	-1.94 ***	-1.94 ***
Female*Age^2/100	4.61 ***	5.31 ***
Female*Age^3/1000	-0.36 ***	-0.45 ***
Age=16 or 17	-2.19 ***	-1.86 ***
Age=16 or 17 * Time trend	-0.05 **	-0.04 **
Female, ages 18-24	-2.88 ***	-2.87 ***
Female, ages 25-34	-0.82 ***	-0.82 ***
Students, seeking job	30.65 ***	30.68 ***
Students, like work	13.36 ***	13.37 ***
Students, not like	1.23 ***	1.25 ***
Looking after family, like work	1.08 ***	1.09 ***
Looking after family, not like	-5.53 ***	-5.52 ***
Discouraged, like work	11.56 ***	11.62 ***
Long-term sick, like work	-6.00 ***	-6.01 ***
Long-term sick, not like work	-7.16 ***	-7.16 ***
Others, seeking job	34.12 ***	34.13 ***
Others, want job, like work	17.38 ***	17.39 ***
	RMSE=29.3 n= 371,862	RMSE=29.3 n= 371,862

Statistical significant coefficients at 90, 95 and 99% confidence levels are noted by one, two and three asterisks respectively. Both specifications also include 3 quarter dummy variables to pick up the seasonal pattern in transitions. Coefficients and the RMSE are multiplied by 100 to make consistent with published activity rates.

Table C: Linear probability models of transition to inactive status

Variable	Unconstrained	Constrained
Detrended GDP	3.57 **	-8.43 (NA)
Higher Degree	-0.19 ***	-0.18 ***
Higher Vocational Training	-0.28 ***	-0.28 ***
A Level	2.05 ***	2.06 ***
Vocational Training	-0.43 ***	-0.40 ***
Apprenticeship	-0.24 ***	-0.24 ***
Lower Education	0.08	0.20 **
Age	-0.44 ***	-0.45 ***
Age^2/100	0.15	0.16
Age^3/1000	0.07 ***	0.07 ***
Female	2.96 ***	2.98 ***
Female*Age/10	-0.03 ***	-0.03 ***
Unemployed*Age/10	0.51 ***	0.51 ***
Unemployed*Age^2/100	-1.60 ***	-1.60 ***
Unemployed*Age^3/1000	0.17 ***	0.17 ***
Age=16 or 17	2.81 ***	2.82 ***
Female, ages 18-24	0.12	0.12
Female, ages 25-34	0.63 ***	0.62 ***
Age>=50	-1.01 ***	-1.22 ***
Self-employed	0.52 ***	0.51 ***
Gov. employment	1.64 ***	1.61 ***
Family employment	14.87 ***	14.85 ***
Unemployed, 0-5 months	9.60 ***	9.63 ***
Unemployed, 6-11 months	7.15 ***	7.15 ***
Unemployed, 12-17 months	6.19 **	6.18 **
Unemployed, >18 months	2.69 **	2.58 **
Lower Education *time trend/10	0.01 **	0.03 ***
Unemployed, >18 months*time	0.12 ***	0.12 ***
Age>=50 * time trend*10	-0.02 ***	-0.01 *
	RMSE=16.47 n= 1,380,253	RMSE=16.47 n= 1,380,253

Statistical significant coefficients at 90, 95 and 99% confidence levels are noted by one, two and three asterisks respectively. Both specifications also include 3 quarter dummy variables to pick up the seasonal pattern in transitions.

Table D: Linear probability models of transition to active status: split periods

Variable	Full sample	1994q1-1997q4	1998q3-2001q2
Detrended GDP	-8.71 (NA)	-8.71 (NA)	-8.71 (NA)
Higher Degree	2.48 ***	1.98 ***	2.95 ***
Higher Vocational Training	1.22 ***	1.04 **	1.23 ***
A Level	0.05	-0.59 *	0.61 *
Vocational Training	1.89 ***	1.31 **	2.18 ***
Apprenticeship	-0.19	-0.50	0.01
Lower Education	-2.15 ***	-2.53 ***	-2.05 ***
Age	-2.17 ***	-1.67 ***	-2.16 ***
Age^2/100	4.60 ***	0.33 ***	0.46 ***
Age^3/1000	-0.36 ***	-0.36 ***	-0.36 ***
Female	19.88 ***	27.26 ***	19.88 ***
Female*Age	-1.94 ***	-2.56 ***	-1.91 ***
Female*Age^2/100	5.31 ***	0.68 ***	0.53 ***
Female*Age^3/1000	-0.45 ***	-0.55 ***	-0.45 ***
Age=16 or 17	-1.86 ***	1.44	-0.86 ***
Age=16 or 17 * Time trend	-0.04 **	-0.33 ***	0.27 ***
Female, ages 18-24	-2.87 ***	-3.77 ***	-2.58 ***
Female, ages 25-34	-0.82 ***	-1.25 ***	-0.53
Students, seeking job	30.68 ***	28.51 ***	30.39 ***
Students, like work	13.37 ***	12.08 ***	13.60 ***
Students, not like	1.25 ***	0.13	1.55 ***
Looking after family, like work	1.09 ***	1.51 ***	0.59
Looking after family, not like	-5.52 ***	-5.90 ***	-5.33 ***
Discouraged, like work	11.62 ***	13.72 ***	8.87 ***
Long-term sick, like work	-6.01 ***	-6.06 ***	-6.06 ***
Long-term sick, not like work	-7.16 ***	-7.40 ***	-7.03 ***
Others, seeking job	34.13 ***	34.47 ***	32.38 ***
Others, want job, like work	17.39 ***	17.13 ***	16.95 ***
	RMSE=29.3 n= 371,862	RMSE=29.7 n= 155,420	RMSE=28.8 n= 140,415

Statistical significant coefficients at 90, 95 and 99% confidence levels are noted by one, two and three asterisks respectively. Both specifications also include 3 quarter dummy variables to pick up the seasonal pattern in transitions. Coefficients and the RMSE are multiplied by 100 to make consistent with published activity rates.

Table E: Linear probability models of transition to inactive status: split periods

Variable	Constrained	1994q1-1997q4	1998q3-2001q2
Detrended GDP	-8.43 (NA)	-8.43 (NA)	-8.43 (NA)
Higher Degree	-0.18 ***	-0.08	-0.24 ***
Higher Vocational Training	-0.28 ***	-0.09	-0.38 ***
A Level	2.06 ***	2.33 ***	1.91 ***
Vocational Training	-0.40 ***	-0.31 **	-0.53 ***
Apprenticeship	-0.24 ***	-0.11	-0.32 ***
Lower Education	0.20 **	0.11	-0.57 **
Age	-0.45 ***	-0.24 ***	-0.48 ***
Age^2/100	0.16	0.04 *	0.02
Age^3/1000	0.07 ***	0.12 ***	0.07 ***
Female	2.98 ***	3.09 ***	2.69 ***
Female*Age/10	-0.03 ***	-0.02 ***	-0.03 ***
Unemployed*Age/10	0.51 ***	0.67 ***	0.44 ***
Unemployed*Age^2/100	-1.60 ***	-0.20 ***	-0.16 ***
Unemployed*Age^3/1000	0.17 ***	0.21 ***	0.18 ***
Age=16 or 17	2.82 ***	3.68 ***	2.27 ***
Female, ages 18-24	0.12	0.16	0.29
Female, ages 25-34	0.62 ***	0.64 ***	0.65 ***
Age>=50	-1.22 ***	-1.52 ***	-0.79 ***
Self-employed	0.51 ***	0.50 ***	0.55 ***
Gov. employment	1.61 ***	1.35 ***	1.95 ***
Family employment	14.85 ***	14.83 ***	14.19 ***
Unemployed, 0-5 months	9.63 ***	6.62 ***	12.14 ***
Unemployed, 6-11 months	7.15 ***	4.33 ***	9.61 ***
Unemployed, 12-17 months	6.18 **	3.70 **	9.31 **
Unemployed, >18 months	2.58 **	0.93 *	-6.10 **
Lower Education *time trend/10	0.03 ***	0.03 **	0.03 ***
Unemployed, >18 months*time	0.12 ***	0.10 **	0.48 ***
Age>=50 * time trend*10	-0.01 *	0.02	-0.02
	RMSE=16.47 n= 1,380,253	RMSE=16.85 n= 578,079	RMSE=16.08 n= 521,524

Statistical significant coefficients at 90, 95 and 99% confidence levels are noted by one, two and three asterisks respectively. Both specifications also include 3 quarter dummy variables to pick up the seasonal pattern in transitions.

Table F: Comparing out-of-sample forecasts

	Combined approach		**Alternatives**			
			KF trend		HP filter	
n-step ahead	Mean	Standard error	Mean	Standard error	Mean	Standard error
1	0.00	0.10	0.00	0.10	-0.12	0.19
4	0.00	0.24	-0.01	0.25	-0.23	0.26
8	-0.03	0.19	-0.06	0.25	-0.45	0.22

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