# Forecasting inflation using labour market indicators

*Vincenzo Cassino**
*and*
*Michael Joyce***

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**Author for correspondence.

Monetary Analysis, Bank of England, Threadneedle Street, London EC2R 8AH.
* enzo.cassino@bankofengland.co.uk
** mike.joyce@bankofengland.co.uk

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**Abstract**

There are a large number of labour market indicators that could be used by monetary policy makers to assess the state of the labour market and the associated implications for inflationary pressure. This paper attempts to assess their relative merits by evaluating their past performance in forecasting movements in price and wage inflation. This is done by considering both their *ex post* performance in predicting inflation – using conventional in-sample Granger causality tests – and their performance *ex ante* – using simulated out-of-sample forecasting tests over the period 1985-2000, based on both recursive and rolling-window estimation. These criteria lead to rather different conclusions. In sample, most labour market indicators appear to be statistically significant in an inflation-forecasting equation, but out of sample a much smaller number of labour market indicator models are better at forecasting inflation than a simple autoregression, with virtually none outperforming this benchmark over the period since 1995. The labour market indicator models that perform relatively well out of sample tend to be sensitive to the precise choice of inflation measure, sample period and estimation method, though there is some evidence that pooling across individual forecasts produces more reliable results. One apparently robust result, however, is that the unemployment rate gap, the most commonly used measure of labour market tightness, performs poorly in out-of-sample forecasts across a range of specifications.

Key words: Labour market, indicators, forecasting, inflation.

JEL classification: C53, E31, J00.

**Summary**

There are a large number of labour market indicators that could be used by monetary policy makers to assess the state of the labour market and the associated implications for inflationary pressure. A non-exhaustive list, taken from recent Bank of England *Inflation Reports*, would include the unemployment rate (measured from both claimant count and the Labour Force Survey), the employment rate, the non-employment rate, measures of skill shortages, and the ratio of vacancies to unemployment. This paper attempts to shed some light on how much weight should be attached to these and other labour market indicators by evaluating them against a simple criterion: their past performance in predicting price and wage inflation.

We compare the performance of 30 labour market indicators (derived from 16 underlying labour market variables) in forecasting three different price and wage inflation measures – based on the RPIX, the DGI-RPIX and the AEI – over various sample periods from the mid-1970s to 2000. To model the relationship between inflation and each labour market indicator, we estimate a reduced-form inflation equation ('a backward-looking Phillips curve'), in which the change in inflation is specified as a data-determined function of past inflation, the labour market indicator itself and (in the case of RPIX and nominal earnings growth) real import price inflation. Where appropriate, we derive our indicator measures by first detrending the underlying labour market variable using a Hodrick-Prescott filter to form a 'gap' measure (ie an estimate of how far the variable is away from its trend) but, as a cross-check, we also separately examine the effect of using the first difference of the variable.

Two basic approaches are used to assess the inflation-forecasting properties of each labour market indicator. We examine their *ex post* forecast performance, by carrying out Granger causality tests based on data from the mid-1970s onwards, to see whether the indicators provide any information about movements in inflation not captured by the past history of inflation itself and (where appropriate) real import price inflation. Since they are backward looking, however, these tests do not tell us how useful particular labour market indicators would have been in genuine forecast situations. We therefore also consider the *ex ante* forecast performance of the indicators, using simulated out-of-sample forecasting tests for the period 1985-2000. This procedure involves adding each of our selected labour market indicators to an inflation-forecasting equation that is estimated, either recursively or over a rolling sample, moving forward the end of the sample period one quarter at a time. The lag lengths of the variables in the equation are re-optimised over each period and the equation is used to forecast out of sample. By limiting our information set to data only available at the time of the forecast,

this method should provide a better approximation to how the models would have predicted inflation in 'real time'. We then compare the out-of-sample forecasts of these indicator models with predictions from an autoregressive model of inflation and with other simple benchmark models.

The in-sample and out-of-sample criteria lead to rather different conclusions about the forecasting performance of the different indicators. According to the in-sample Granger causality analysis, most labour market indicators appear to be statistically significant in an inflation-forecasting equation. However, the out-of-sample forecasting analysis suggests that a much smaller number of labour market indicator models are better at forecasting changes in inflation than an autoregressive model, and that virtually none outperform this benchmark over the period since 1995. Moreover, the individual labour market indicator models that perform relatively well out of sample tend to be sensitive to the precise choice of inflation measure, sample period and estimation method. Interestingly, one seemingly robust result is that the unemployment rate gap, the most commonly used measure of labour market tightness, performs poorly across a range of specifications.

There are a number of possible reasons for the poor out-of-sample performance of most of the labour market indicator models examined. One contributory factor is that neither the Hodrick-Prescott or difference filters are likely to do a good job in capturing the time-varying trend of the underlying labour market variable. However, general model instability and overfitting in the estimation also contribute, probably reflecting the reduced-form nature of the analysis, which makes it vulnerable to structural and policy changes, as well as to changes in the pattern of shocks hitting the economy. Since no specific indicators are superior in all circumstances, we suggest that the best approach is to take into account a wide variety of information in forming an assessment of the labour market, in line with current practice. This conclusion is reinforced by the fact that simple combination forecasts, based on taking the median or trimmed mean of forecasts based on the individual indicator models, generally produce more reliable results.

# 1. Introduction

There are a large number of labour market indicators that could be used by monetary policy makers to assess the state of the labour market and the associated implications for inflationary pressure. A non-exhaustive list, taken from recent Bank of England *Inflation Reports*, would include the unemployment rate (measured from both claimant count and the Labour Force Survey), the employment rate, the non-employment rate, measures of skill shortages, and the ratio of vacancies to unemployment. This paper attempts to shed some light on how much weight should be attached to these and other labour market indicators by evaluating them against a simple criterion: their past performance in predicting price and wage inflation.

We examine the performance of 30 different labour market indicators (derived from 16 underlying labour market variables) in forecasting three different price and wage inflation measures – based on the RPIX, the DGI-RPIX and the AEI – over different sample periods. We use two basic approaches. We first examine the leading indicator properties of labour market variables using conventional Granger causality tests based on full-sample information. More precisely, we ask if, looking back over the period since the early 1970s, these indicators have contained any incremental information about future inflation over and above that contained in past information on inflation itself. Of course, these tests tell us about the *ex post* correlation of labour market indicators and inflation; they do not tell us how useful these indicators would have been in genuine forecast situations. We therefore supplement these backward-looking tests with a forward-looking analysis, based on the simulated out-of-sample forecasting method developed by Stock and Watson (1999), (2001), applied to the period 1985 to 2000. This involves adding each of our selected labour market indicators to a reduced-form inflation equation that is estimated, either recursively or using a rolling window, through time. The equation specification is re-optimised each period and used to forecast out of sample. This process is then repeated, extending the sample one quarter at a time. By limiting our information set to data only available at the time of the forecast, we should be better able to assess how well these models would have predicted inflation in 'real time', which is the more relevant yardstick for monetary policy makers. [(1)]

Since the basis of our analysis is an inflation-forecasting regression that relates changes in nominal wage and price inflation to some measure of labour market excess demand or

[(1)] An important caveat to this statement is that we do not examine the vintages of data that would have been available to policy-makers in real time, as in eg Orphanides and van Norden (1999), so the tests are properly described as simulated or quasi out-of-sample forecasts.

disequilibrium, our results can also be interpreted as examining the robustness of the 'Phillips curve' relationship, at least in its backward-looking form. So, in principle, they should also provide evidence on whether unemployment or some other measure of labour market 'tightness' provides the best measure to use in a wage or price Phillips curve of this form.(2)

It needs to be emphasised, however, that since our analysis is based on a reduced-form approach, our findings will be vulnerable to changes in policy regime and other forms of structural change, as well as to changes in the pattern of shocks hitting the economy. Indeed, as is well known, the fact that such reduced-form relationships subsume the monetary authorities' reaction function means that finding that a given indicator was not correlated with future inflation outturns might even indicate that policy-makers had been using it optimally in setting policy (see eg Cecchetti (1995)). To try to mitigate this particular problem, we consider the predictive content of labour market indictors over a relatively short horizon, up to a year ahead, which is less likely to be affected by the reaction of the authorities. But even taking these caveats as given, we would argue that the results of the analysis could still be potentially useful, *inter alia*, in identifying indicator models, which can be used as cross-checks on the inflation forecasts from other, more structural, models.(3)

The rest of the paper is structured as follows. We begin in Section 2 with a brief look at which labour market tightness measures might be expected to be associated with inflationary pressure. Section 3 describes our basic data and how we transformed the data to derive a range of 'gap' measures. Section 4 sets out the empirical methodology we use to assess the forecasting performance of our indicators. Our results are reported in Section 5. We first describe the results of in-sample tests and then go on to discuss forecast tests based on both recursive and rolling window regression out-of-sample forecasts. Section 6 concludes.

## 2. Inflation and indicators of labour market 'tightness'

Before discussing which labour market indicators might *a priori* be expected to forecast future inflation, it is worth first touching on why we should expect to observe any correlation at all.

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(2) Brigden and Thomas (2003) provide an extensive discussion of the concept of labour market 'tightness', which we return to below.

(3) The problems with backward-looking Phillips curves are well known and we shall touch on them below. Nevertheless, these models are still widely used and indeed make up part of the Bank's own suite of forecasting models (see Bank of England (1999)).

A short-run relationship between some disequilibrium measure of real activity and inflation is, of course, one of the defining characteristics of the Phillips curve. A generic representation of such a relationship might take the following form:

$$\pi_t = \alpha(L)\, \pi^e_t + \beta(L)\, \pi_{t-1} + \gamma(L)\, (A_t - A^*_t) + \eta(L)\, z_t \qquad \textbf{(2.1)}$$

where $\pi_t$ is the rate of price or wage (unit labour cost) inflation; $\pi^e_t$ is the expected rate of price/wage (unit labour cost) inflation; $A_t$ is a measure of real activity; $A^*_t$ is the natural or equilibrium level of real activity in steady state; $z_t$ represents other factors, eg supply-side shocks; $\alpha(L)$ is a forward polynomial; and $\beta(L)$, $\gamma(L)$ and $\eta(L)$ are backward polynomials in the lag operator $L$. Note that $\alpha(L)$ and $\beta(L)$ need to sum to unity if there is to be no long-run trade-off between inflation and activity.

Although the theoretical underpinnings of the Phillips curve are contentious, relationships of a similar form to **(2.1)** emerge as a reduced form from a variety of theoretical models (see eg Astley and Yates (1999) and the references cited therein).(4) The necessary ingredient in getting a relationship between a real activity measure and inflation is an assumption of some form of nominal rigidity, typically in either the labour or the product market. Depending on the precise details of the underlying model, the activity term in the equation may then be written either in terms of a measure of labour market disequilibrium (typically, but not exclusively, the unemployment rate), in terms of an output gap, or in terms of capacity utilisation (or less commonly some combination of all three).

In this paper, we are obviously concerned with the relationship between inflation and measures of *labour market* disequilibrium, or 'tightness'. Following Brigden and Thomas (2003), a helpful way of thinking about labour market tightness is as an out of steady-state phenomenon, reflecting a temporary imbalance between the demand and supply of labour. This is obviously a difficult concept to measure and, as Brigden and Thomas also note, different theories of the labour market suggest different proxies for it. The approach we take in this paper is deliberately eclectic, however, in appealing both to theory and to previous empirical work, in justifying the candidate indicators we examine. We now discuss each of these briefly in turn.

(4) Since the Phillips curve is not a structural relationship, there are strong *a priori* reasons for thinking that it may not be stable over time and may therefore be ineffective as a forecasting tool. The purpose of this study is, of course, in large part to assess this empirically.

### *Measures of labour market tightness*

#### *Unemployment rate (searchers, claimants, male claimants)*

The unemployment rate, or the difference between the unemployment rate and some measure of the equilibrium unemployment rate,[5] is perhaps the most widely used measure of labour market tightness, since it emerges from a variety of theoretical models and has been used in countless empirical studies of the Phillips curve, starting of course with Phillips himself (1958). We shall consider two main measures of the unemployment rate. The search-based measure from the Labour Force Survey, which reflects whether individuals have been searching for work over the past four weeks and are available to start work in the next two weeks, and the claimant count measure, which is based purely on the numbers claiming benefits related to unemployment. Because of the possibility that the level of female unemployment may be distorted (eg the rules on benefit entitlement and social convention may make unemployed married women less likely to claim), we also consider the male (claimant) unemployment rate on its own (a practice followed by, eg Layard and Nickell (1985, 1986)).

#### *Unemployment duration (short-term unemployment, logged unemployment rate)*

A variety of theories suggest that the duration structure of the unemployed pool is relevant to gauging the inflationary signals emerging from the labour market. In particular, the long-term unemployed are often thought to have less of a restraining influence on inflation than the short-term unemployed, because their relative prospects of finding employment are worse. The lower employability of the long-term unemployed is usually related to two factors: first, that their characteristics tend to be poorer in terms of education and other skills; and second, that the experience of being unemployed has a scarring effect, either because employers use it as a screening device or because skills are lost as unemployment duration lengthens. For this reason, it has been common simply to exclude the long-term unemployed and focus solely on the short-term (usually six months or less) unemployment rate. An alternative measure that is sometimes used for the same reason is the logarithm of the unemployment rate (see eg Layard and Nickell (1985, 1986)), on the argument that the proportion of short-term unemployed in the total stock is likely to be lower at higher rates of unemployment, so that a larger absolute change in the unemployment rate is required to have the same restraining effect on inflation, as

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(5) See eg Layard, Nickell and Jackman (1991). The issue of how to measure the 'equilibrium' unemployment rate is obviously extremely important (see below).

unemployment rises. Of course, using the log of the unemployment rate might also be justified more generally by the belief that the Phillips curve is non-linear.

***Non-employment and weighted non-employment rate***

The use of non-employment rather than unemployment as a measure of labour market tightness may be motivated by the fact that that those out of the labour force may nevertheless be part of the relevant pool of people who are available to fill employers' vacancies. Schweitzer (2003) shows that some groups of the inactive are more likely to move into employment in the next quarter than the typical unemployed person. This fact has led to the Bank of England (see eg the Bank of England (2000)) deriving a weighted non-employment index, which combines together different categories of the unemployed and inactive population, according to their relative transition rates into employment. We examine both the working-age non-employment rate and the weighted non-employment index in our analysis.

***Ratio of vacancies to unemployment (stock and stock/flow-based measures)***

Search and matching theories of unemployment (eg Pissarides (2000)) put an emphasis on the ratio of the total stock of vacancies to the total stock of unemployment as a natural measure of labour market tightness. If we think of vacancies as measuring unmet labour demand and unemployment as representing the pool of labour available to fill those vacancies, then the ratio of the two (the VU ratio) might be thought to provide a measure of the degree of difficulty firms face in recruiting labour. And, other things being equal, we might expect increases in this ratio to be associated with greater inflationary pressures.

There are a number of difficulties with the VU ratio as an indicator of tightness, however. One problem with it is that it is susceptible to structural change. A fall in the equilibrium unemployment rate (eg due to labour market reforms) will lead to a higher VU ratio which has nothing to do with labour market tightness *per se*. This problem is hardly unique to the VU ratio, of course, (the steady-state values of any labour market variable may change over time) and since we detrend the ratio in our econometric work (see below) we arguably take some account of this.

Another problem with the ratio, raised by Coles and Smith (1998), stems from the fact that an unemployed worker can search over the available stock of vacancies in a relatively short period of time. So if someone remains unemployed, it can be inferred that they are not suited to any of the vacancies currently on offer. By this argument, the existing stock of vacancies can only be filled by newly unemployed workers. It also follows that the existing stock of unemployed can only be matched by new vacancies. This suggests two alternative VU measures: the ratio of new vacancies to the stock of unemployment and the ratio of the stock of vacancies to the inflow to unemployment. We examine all three vacancy-unemployment ratios in our empirical work.

***Unemployment flows (inflow rate, outflow rate)***

Search-based theories of unemployment tend to place more weight on flow measures of unemployment than on the stock. If workers are concerned with their outside option, they will focus on the probability of being re-employed and this has been used to justify focusing on outflow rate from unemployment, rather than the unemployment rate. Efficiency wage models in which wages are set to prevent shirking also suggest that the probability of exiting unemployment will be a better measure of labour market tightness (see eg Blanchard and Katz (1997)[(6)]). Some authors (Burgess and Turon (2000)) have argued, however, that the empirical evidence shows the inflow rate to be more responsive to aggregate shocks than the outflow rate, which suggests the inflow rate may also potentially be a useful indicator of tightness. We examine both unemployment outflow and inflow rates in our analysis.

***Employment growth***

It has sometimes been argued that the Phillips curve formulation due to Friedman (1968) is more naturally expressed in terms of employment rather than unemployment. This is because the theory underlying the relationship is in terms of underestimation (overestimation) of price inflation leading to more (fewer) people *working*, as the real wage is expected to be higher (lower) than it turns out *ex post*. Whether this translates into lower (higher) unemployment depends on what happens to labour force participation and, since the latter is affected by a variety of factors, the unemployment rate itself may not be the best indicator of demand shocks. For this reason, Levi and Makin (1980), for example, focus on the percentage change in employment in their Phillips curve analysis, rather than the unemployment rate. While the Phillips curve equation Levi and Makin estimate has employment growth as the dependent variable, rather than inflation, the general point that demand shocks are better measured in terms of employment growth rates rather than unemployment would seem just as applicable to an inflation-based

(6) Blanchard and Katz define the unemployment exit rate in terms of the ratio of total hires to the stock of unemployment. The unemployment exit rates we are able to construct are of necessity constructed solely from data on unemployment outflows, in the absence of a long enough time series data on all job matches, including flows from those in employment and those classified as inactive.

Phillips curve. We therefore include employment growth rate as one of the indicators we examine.

### *Skill mismatch*

Measures of mismatch have often been used to explain wage growth, following the influential work of Layard and Nickell (1985), (1986). The intuition for this is that larger mismatches by region, occupation or skill will mean that demand shocks get translated into greater aggregate wage pressures, if at the micro-level wages are less responsive to a given-sized demand shock as the amount of labour slack increases (ie wage curves are non-linear). Measures of skill mismatch have generally been the most successful in empirical work. For example, Bean and Pissarides (1991) find that a measure of skill mismatch based on the CBI survey 'appears to be a better indicator of labour market pressures than the unemployment rate'. We report results using this measure below.(7)

### *Labour share of income*

The recent literature on the so-called New Keynesian Phillips curve (see eg Gali, Gertler and Lopez-Salido (2000)) derives a Phillips curve relationship between inflation and the current and future values of real unit labour costs or, equivalently, the labour share of income, expressed as deviations from steady state. The basic intuition is that, in a world of costly price adjustment, firms take into account current and expected real marginal costs when taking their pricing decisions. Given Cobb-Douglas technology, this simplifies to firms focusing on their real unit labour costs. The greater the deviation of real unit labour costs from steady state, the greater the incentive for firms to raise prices. Batini, Jackson and Nickell (2000) derive and estimate a similar relationship for the United Kingdom and suggest that the labour share contains useful information that predicts future inflation; a finding also consistent with recent research on UK New Keynesian Phillips curves by Balakrishnan and Lopez-Salido (2002). We examine the two measures of the labour share favoured by Batini *et al* (*op cit*) in their empirical work: a whole-economy measure which includes an adjustment for self-employment (termed $s_L$ in their paper), and a second measure that includes the self-employment adjustment but excludes the public sector (termed $s^*_L$ in their paper).

(7) Burriel-Llombart and Thomas (2001) argue that this measure does not capture skill mismatch well, although it does seem to do a good job in picking up the economic cycle. As an alternative, we experimented with the ratio measure of CBI skilled to unskilled labour shortages favoured by Nickell and Bell (1995), but found that it performed worse than the skilled measure in our inflation-forecasting regressions.

## 3. Data

In this section, we provide a brief description of our data set (a more detailed explanation of how each series was constructed is contained in Annex A). All our data run from the early 1970s to 2000 Q2 and, where available, are seasonally adjusted. [8] We used the latest vintage of the data available to us, so (as noted above) our out-of-sample forecast tests do not strictly emulate the real-time data that would have been available to policy-makers at the time (eg as in Orphanides and van Norden (1999)). For our purposes, that is unnecessary because we do not wish to infer anything about what policy-makers should or could have forecast over the past.

### *Inflation measures*

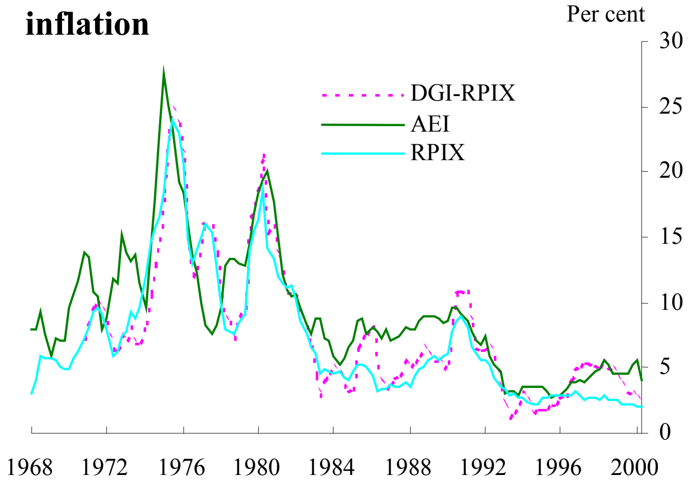
Our analysis is based on three different measures of price/wage inflation derived from the retail price index excluding mortgage payments (RPIX), the Bank of England's domestically generated inflation RPIX measure (DGI-RPIX) and the Average Earnings Index (AEI) (see Chart 3.1). If we think of inflation as being composed of a weighted average of domestically generated inflation and imported inflation, it seems clear that we would expect labour market indicators to predict the former rather than the latter. And given the openness of the UK economy, we need to control for the influence of external shocks in our analysis if we are to gain any insight into the incremental explanatory power of labour market indicators in predicting inflation. The Bank's DGI-RPIX measure is, in principle, ideally suited for what we require, in that it mechanically strips out the direct impact of import prices (see Bank of England (1998)), though there is some evidence that it does so incompletely (see eg Balakrishnan and Lopez-Salido (2002)). We also look at RPIX directly, but in this case also include real import price inflation as an additional regressor in our forecasting model.

An obvious alternative DGI measure is unit labour cost growth (ie the difference between labour cost and productivity growth per head), but since productivity growth itself is quite volatile, it may be preferable to measure unit labour costs using trend rather than actual productivity growth. This is the basis of the Bank's DGI-ULC measure, which assumes a fixed trend rate of productivity growth of 2%. We use AEI growth rather than DGI-ULC, however, because the predictive properties of the latter should be virtually identical to the AEI, given the assumption that trend productivity growth is fixed. In our forecasting model for AEI inflation, we also include real import price inflation as an additional regressor, to control for the influence of

[8] The main exceptions were the data for DGI-RPIX and RPIX. To allow for possible seasonality, we included deterministic seasonal dummy variables in our models of DGI-RPIX and RPIX inflation.

external shocks on the wedge between real producer and consumer wages (so-called wedge effects[9]).

**Chart 3.1 DGI-RPIX, RPIX and AEI annual inflation**




### *Labour market variables*

The 16 basic labour market variables used in our analysis are set out in the first column of Table 3.1 and illustrated in Charts 3.2-3.16. It is clear from the time series plots that most of these variables are strongly trended and formal unit root tests reported in Annex B suggest that, with the exception of one of the labour share variables, we can reject the hypothesis that they are non-stationary. For our regression analysis, we therefore need to transform them in some way to ensure that they are stationary. [10]

Quite apart from the econometrics, theory suggests that labour market tightness is an out-of-steady-state concept, so that is the deviation from long-run equilibrium that is most relevant in determining inflationary pressure. This suggests we should use ‘gap’ measures for each of our indicators. On the grounds of tractability, we derived these using a purely statistical approach, which involved estimating trends for each indicator using the Hodrick-Prescott (HP) filter, with a smoothing parameter of 1600 (the conventional setting for quarterly data). (The full-sample gap measures are illustrated in Charts 3.17-3.30.)

There are, of course, well-known problems with using statistical procedures to measure economic concepts. Moreover, even as a statistical trend extraction method, the HP filter is problematic because of the so-called end-point problem – the fact that the filter relies on future (and past)

[9] See Layard, Nickell and Jackman (1991).
[10] The only variables we chose not to transform in this way were the two labour share measures: LS and LSXPUB.

values means that it can be particularly unreliable at the end of the sample. This problem is particularly acute in the out-of-sample forecast tests we report here, because it is inevitably here that the results will rely crucially on the most recent outturns. But although it is quite possible that our results might be improved by using a more sophisticated method of detrending, the HP filter is widely used and relatively simple to understand. As a cross-check on our results, we also report the results from deriving our indicators by taking first-differences of the underlying labour market variable.

Taking account of all the transformations to the basic data series into gap and difference measures, we have a total of 30 labour market indicators. In our out-of-sample tests, we shall also supplement them with 'combination forecasts' based on the mean, medium and 10% trimmed mean of our set of individual indicator forecasts. This follows work on the indicator properties of asset prices for GDP growth and inflation by Stock and Watson (2001), who found that pooling individual forecasts resulted in more reliable results, in the sense that these forecasts more consistently outperformed a univariate benchmark model across different specifications and sample periods.

**Table 3.1 Labour market indicators**

| Indicator | Transformations: | | | |
|---|---|---|---|---|
| Definition | Level Variable | | Difference Variable | |
| | Code | Construction | Code | Construction |
| LFS unemployment rate | UR | Gap from HP filter | DUR | Quarterly change |
| Log of LFS unemployment rate | LUR | Gap from HP filter | DLUR | Quarterly change |
| Claimant count unemployment rate | CCR | Gap from HP filter | DCCR | Quarterly change |
| Short-term unemployment rate | STUR | Gap from HP filter | DSTUR | Quarterly change |
| Male unemployment rate | MUR | Gap from HP filter | DMUR | Quarterly change |
| Unemployment inflow rate | UIR | Gap from HP filter | DUIR | Quarterly change |
| Unemployment outflow rate | UOR | Gap from HP filter | DUOR | Quarterly change |
| Non-employment rate | NER | Gap from HP filter | DNER | Quarterly change |
| Weighted non-employment rate | WNER | Gap from HP filter | DWNER | Quarterly change |
| Log of number of workforce jobs | LJOBS | Gap from HP filter | DLJOBS | Quarterly log change |
| Ratio of vacancies to unemployment | VU | Gap from HP filter | DVU | Quarterly change |
| Ratio of new vacancies to the stock of unemployment | VIU | Gap from HP filter | DVIU | Quarterly change |
| Ratio of vacancies to unemployment inflows | VUI | Gap from HP filter | DVUI | Quarterly change |
| CBI measure of skill shortages | SKILL | Gap from HP filter | DSKILL | Quarterly change |
| Labour share adjusted for self-employment | LS | Level | | |
| Labour share adjusted for self-employment and excluding the public sector | LSXPUB | Level | | |

Note: The construction of each of our indicators is explained more fully in Annex A.

**Chart 3.2** LFS unemployment rate (UR)

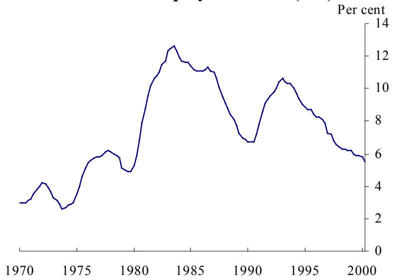



**Chart 3.3** Logged LFS unemployment rate (LUR)

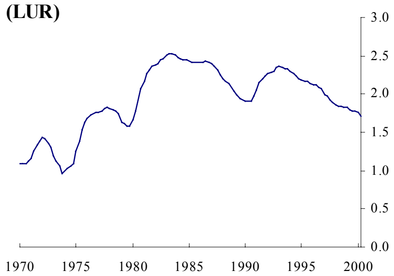



**Chart 3.4** Claimant count unemployment rate (CCR)

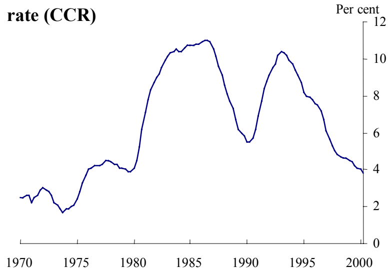



**Chart 3.5** Male unemployment rate (MUR)

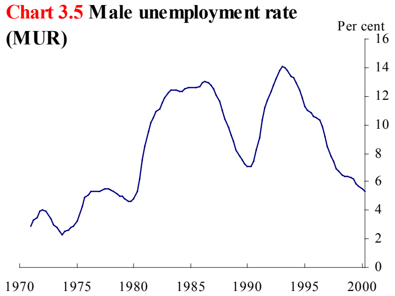



**Chart 3.6** Short-term unemployment rate (STUR)

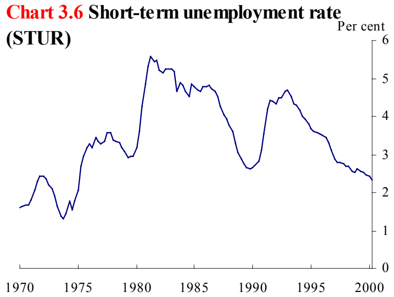



**Chart 3.7** Unemployment inflow rate (UIR)

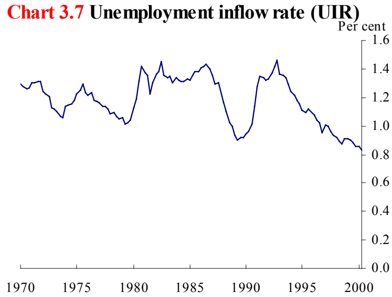



**Chart 3.8** Unemployment outflow rate (UOR)

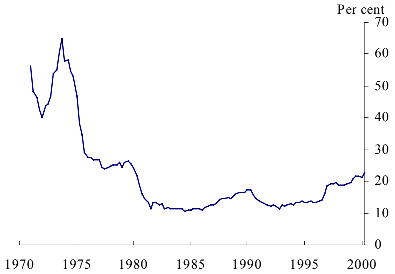



**Chart 3.9** Non-employment rate (NER)

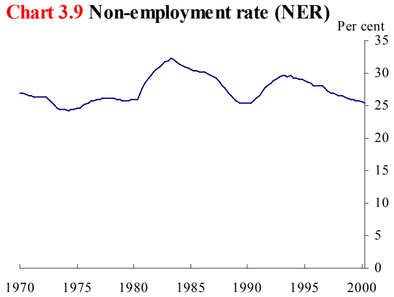



**Chart 3.10** Weighted non-employment rate index (WNER)

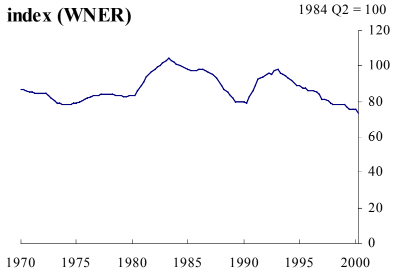



**Chart 3.11** Logged number of workforce jobs (LJOBS)

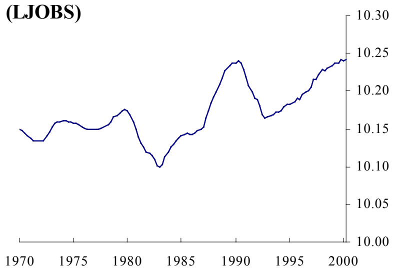



**Chart 3.12** Ratio of vacancies to unemployment (VU)

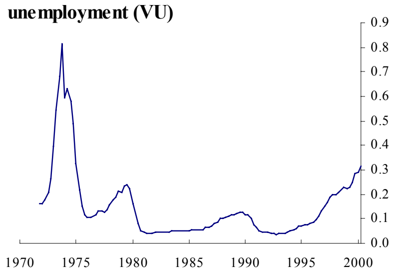



**Chart 3.13** Ratio of new vacancies to unemployment (VIU)

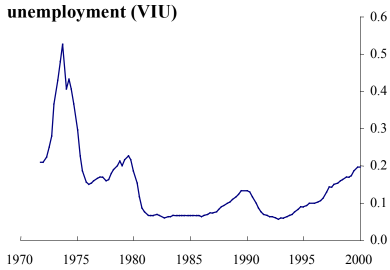



**Chart 3.14** Ratio of vacancies to unemployment inflows (VUI)

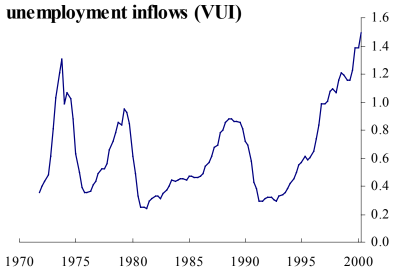



**Chart 3.15** CBI skill shortages (SKILL)

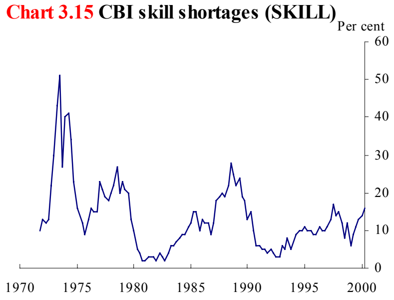



**Chart 3.16** Labour share adjusted for self-employment (LS) and excluding public sector (LSXPUB)

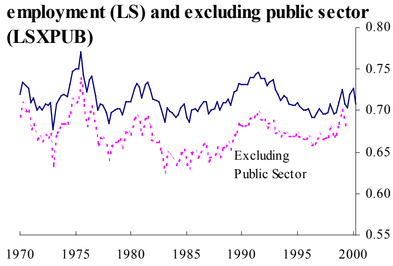


**Chart 3.17** **LFS unemployment rate gap (UR)**

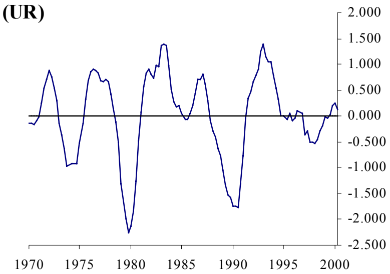



**Chart 3.18** **Logged LFS unemployment rate gap (LUR)**

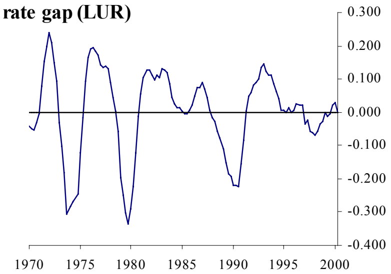



**Chart 3.19** **Claimant count unemployment rate gap (CCR)**

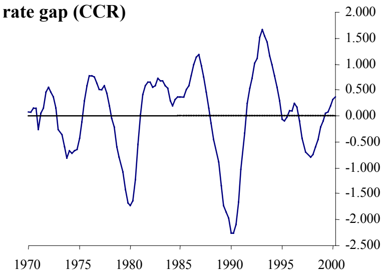



**Chart 3.20** **Male unemployment rate gap (MUR)**

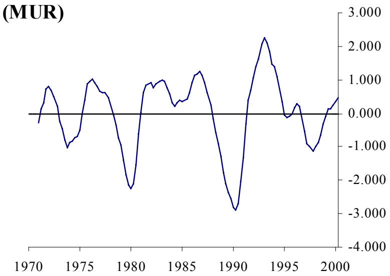



**Chart 3.21** **Short-term unemployment rate gap (STUR)**

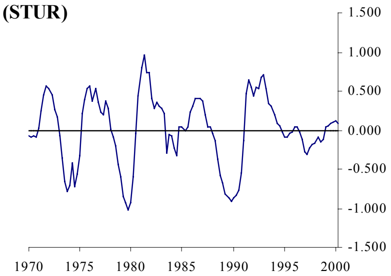



**Chart 3.22** **Unemployment inflow rate gap (UIR)**

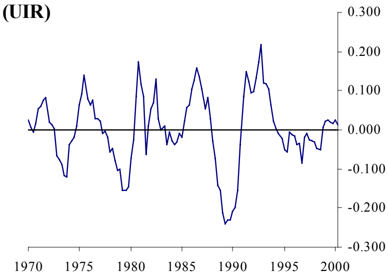



**Chart 3.23** **Unemployment outflow rate gap (UOR)**

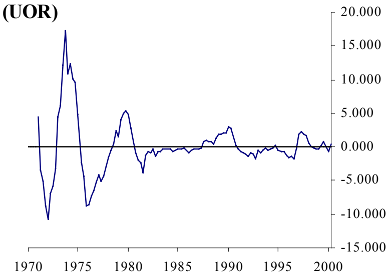



**Chart 3.24** **Non-employment rate gap (NER)**

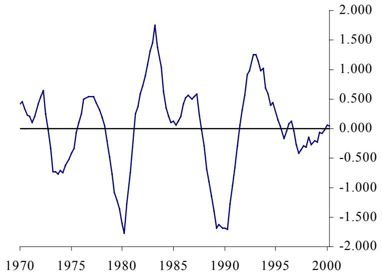



**Chart 3.25** **Weighted non-employment rate gap (WNER)**

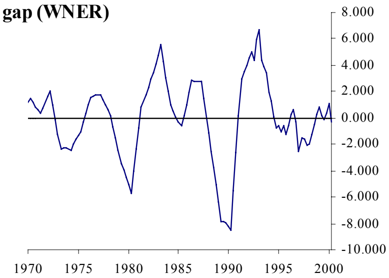



**Chart 3.26** **Logged number of workforce jobs gap (LJOBS)**

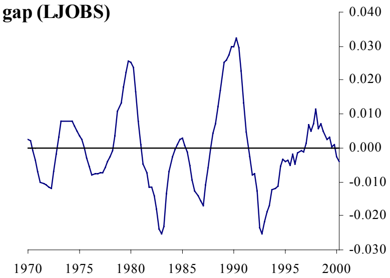



**Chart 3.27** **Ratio of vacancies to unemployment gap (VU)**

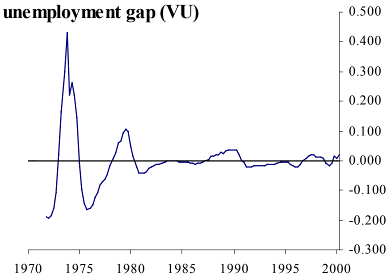



**Chart 3.28** **Ratio of new vacancies to unemployment gap (VIU)**

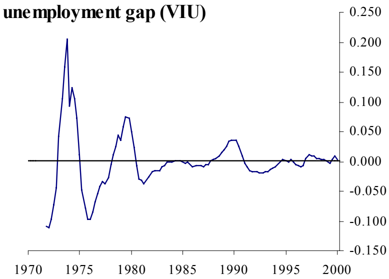



**Chart 3.29** **Ratio of vacancies to unemployment inflows gap (VUI)**

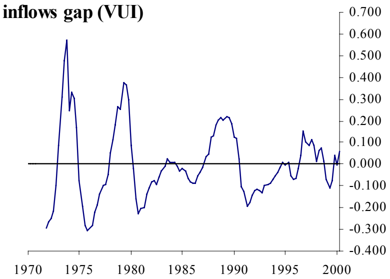
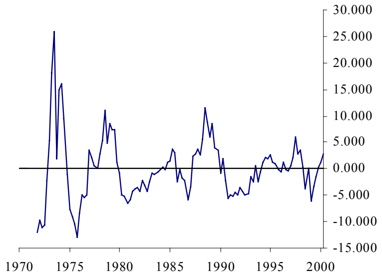



**Chart 3.30** **CBI skill shortages (SKILL)**



## 4. Method

### *4.1 The inflation-forecasting model*

The basis for assessing the forecasting performance of our set of labour market indicators is the following 'Phillips curve' regression (see Stock and Watson (1999)):

$$\pi^h_{t+h} - \pi_t = \alpha + \beta(L)\,\Delta\,\pi_t + \gamma(L)\,I_t + \eta(L)\,z_t + \varepsilon_{t+h} \qquad \textbf{(4.1)}$$

where $\pi^h_{t+h} = (400/h).\ \ln(P_{t+h}/P_t)$ is the annualised inflation rate over the period $t$ to $t+h$ defined in terms of the relevant price/wage index $P_t$; $\pi_t = 400.\ \ln(P_t/P_{t-1})$ is the annualised quarterly inflation rate defined in terms of the same price/wage index; $I_t$ is the labour market indicator being tested; $z_t$ represents annualised quarterly real import price inflation (which is included for the RPIX and AEI models to pick up external shocks); $\varepsilon_{t+h}$ is the error term; and $\beta(L)$, $\gamma(L)$ and $\eta(L)$ are polynomials in the lag operator $L$.[11]

The equation is similar to the reduced-form Phillips curve described in equation **(2.1)**, but there are a few important differences. Perhaps the most obvious difference is that expectations have been substituted out of the equation. This is a common simplification in the empirical literature. It can be justified if it is assumed that expectations are backward-looking or that they can be proxied in terms of lags, which will be valid in the absence of structural change.

A more unusual feature of the equation is that the dependent variable is defined over *h*-quarters ahead. This set-up means that we can look at the forecasting performance of different indicators at horizons greater than one quarter ahead, without the need to also forecast the future value of the indicators themselves using a supplementary model. This has the advantage that our inflation forecast errors are not contaminated by errors from forecasting the indicators themselves.

Another important feature of the equation is that it imposes the restriction that inflation is integrated of order one, so the equation explains changes in inflation, rather than levels of inflation. This I(1) restriction is consistent with the unit root tests for inflation over our sample period. We have looked at the sensitivity of our results to this assumption, but generally found that the models with this assumption had lower forecast errors over our sample, even in the

[11] The model specification also included deterministic seasonals, in cases where the inflation data were not seasonally adjusted (ie DGI-RPIX and RPIX).

period of low inflation since the mid-1990s.[12] We therefore concentrate exclusively on these results in what follows.

The specification also assumes that the indicator variable $I_t$ is stationary, which means in most cases that the underlying labour market variable needs to have been transformed by either detrending to form a 'gap' measure or by first differencing (as discussed in Section 3 above).[13]

### *4.2 In-sample and out-of-sample tests*

As has already been mentioned, we used two approaches to assess the forecasting performance of the indicators: *ex ante* and *ex post*. The *ex post* approach involved running equation **(4.1)** for each of our labour market indicators over our full-sample period, which in most cases extended from the early 1970s to 1999 Q2. Where the selected indicator was a 'gap' measure, the HP filter used to generate it was also run over the full-sample period. In each case, the order of the polynomials $\beta(L)$, $\gamma(L)$ and (where appropriate) $\eta(L)$ was selected optimally according to the Schwartz Information Criterion (SIC), allowing for a maximum of eight lags. We then tested the hypothesis that $\gamma_i = 0$ using a standard F-test. As a test for stability, the preferred specification for each indicator was re-estimated over the second half of the sample from 1985 Q1-1999 Q2 and the F-test $\gamma_i = 0$ was repeated. To examine the sensitivity of the results to the forecast horizon, results were computed for two different horizons, $h$=1 and $h$=4, but in general we found that the indicator models performed best when forecasting changes in inflation over the year ahead. We did not look at longer periods, in order to try to mitigate the problem that our results might be contaminated by policy feedbacks.[14]

To examine the *ex ante*, or out-of-sample, forecasting performance of the indicators, equation **(4.1)** was estimated both recursively and using a rolling window and then used to generate one year ahead forecasts of the change in inflation. The recursive estimates were constructed by first estimating each model up to 1984 Q1. Since $h$ was set to 4, this implied that the regressors in our

(12) This might at first seem surprising since inflation over the mid to late1990s looks much more like a stationary process. The reason for this result seems to be that the pronounced downward trend in inflation over the *estimation* period gets incorporated into the parameters of models which assume inflation is stationary, worsening their forecasting performance over this period.
(13) The fact that we find inflation and most of our labour market indicators non-stationary raises the possibility that there may be cointegrating relationships between them. This in turn might suggest that equation **(4.1)** should be augmented to include an error correction term. However, it seems theoretically unappealing that there should be a long-run relationship between inflation and, say, the rate of unemployment. In fact, when we tested for cointegration, we found that none of our indicators were cointegrated with inflation.
(14) See discussion in Section 1.

model were dated from 1983 Q1 and earlier.(15) The SIC was then used to select the optimal number of lags up to a maximum of eight, on each of the right-hand side variables – the indicator, the change in inflation and where appropriate real import price inflation. The model was then used to forecast four quarters ahead, to 1985 Q1. The process was then repeated, updating the sample periods by one quarter at a time. In each period, the dynamic specification of the model was re-optimised according to the SIC.

To allow for sudden structural breaks in the Phillips curve relationship, we also tried forecasting using a fixed window, which entails dropping observations beyond some prespecified cut-off. For our analysis, we chose a single fixed window length of 40 quarters. Inevitably this is rather arbitrary, but it seems a reasonable compromise between the need to keep the period short enough to accommodate rapid structural changes and long enough to have sufficient degrees of freedom to estimate the model.(16) For these results, we began by estimating each model from 1974 Q1 to 1984 Q1 and then forecasting four quarters ahead. The gap measures were computed as in the recursive case. The sample period was rolled forward one quarter from 1974 Q2 to 1984 Q2, the model specification was re-optimised, and the forecasting exercise was repeated, and so on.

We compare the indicator models in two ways. First, we examine their relative mean squared errors (MSEs), ie the mean squared error of each indicator relative to the MSE from an autoregressive (AR) model which we use as the benchmark. We report relative MSEs over the post-1985 period, and separately in three roughly equal subperiods 1985 Q1-1989 Q4, 1990 Q1-1994 Q4 and 1995 Q1-2000 Q2. To evaluate the statistical significance of the relative MSE statistic, we also report its t-ratio (using standard errors corrected for heteroscedasticity and autocorrelation (HAC) using the Newey-West method (17)) relative to the null that the ratio is unity, ie there is no difference between its MSE and that of the benchmark model. Following Stock and Watson (1999), we also compare the indicator models in terms of the incremental value their forecasts add to the baseline AR model. To do this, we compute the $\lambda$ coefficient in the following forecast encompassing regression:

(15) If the chosen indicator was a gap measure, the HP trend used to *estimate* the model was generated using four quarters of forward information up to 1984 Q1. Restricting the data used to generate the trend to $t$-4 information had no major impact on the results. Note that for the out-of-sample forecast tests, the HP trend was generated using only information up to period $t$.

(16) Pesaran and Timmermann (2000) make the point that a fixed window size will rarely be optimal and propose a method of selecting an optimal time-varying window, according to the size and timing of break points. Because of the difficulty of estimating structural breaks accurately, we have not attempted to apply their methodology here.

(17) We use a truncation lag of 3 to allow for moving-average errors resulting from overlapping observations. To compute the HAC-corrected standard errors, we amended the GAUSS code kindly made available by Stock and Watson, based on their 1999 paper (see References).

$$\pi^h_{t+h} - \pi_t = \lambda f^X_t + (1 - \lambda)\ f^{AR}_t + \varepsilon_{t+h} \qquad \textbf{(4.2)}$$

where $f^X_t$ is the forecast from the model using indicator $X$ and $f^{AR}_t$ is the forecast from an AR model. If $\lambda = 0$ then forecasts based on indicator $X$ provide no incremental information to the AR benchmark. We report $\lambda$ and its HAC-corrected t-ratio.(18)

## 5. Do labour market indicators predict inflation?

### *5.1 In-sample test results*

Tables 5.1.1 to 5.1.3 contain the results from estimating equation **(4.1)** for each of our three measures of inflation over two forecasting horizons: one quarter ahead ($h$=1) and one year ahead ($h$=4). The tables show the p-values from the F-test that all the $\gamma$ terms were zero, derived using HAC-corrected standard errors.

The most striking feature of the results is that, regardless of the inflation measure being forecast, virtually all of our chosen labour market indicators are strongly correlated with the change in inflation at the one-year horizon. Indeed, the high levels of statistical significance for the exclusion tests are such that it is virtually impossible to discriminate among the indicators at this horizon. This result holds for both the full-sample period and for the sub-sample from 1985, though there is some evidence from Chow tests (unreported) that for at least some of the indicators the regressions are unstable if the sample is split at 1985.

Perhaps not surprisingly (given lags in the transmission process and volatility in the data), the results at one quarter ahead are much more patchy, though even here a good many of the indicators are statistically significant. The results differ across each measure of inflation, however. The best results are for explaining the change in AEI inflation one quarter ahead, where about 80% of the indicators are found to be statistically significant at conventional (5%) levels over the full-sample period and around half of the indicators are significant in the sub-sample. The results for DGI-RPIX and RPIX are slightly less impressive in that around two-thirds of the indicators are statistically significant in the full sample, with about a quarter of the indictors for DGI-RPIX and a half for RPIX remaining statistically significant in the sub-sample.

(18) Note that since the models for RPIX and AEI will generally include terms in real import price inflation, the relative MSE statistic and the $\lambda$ statistics for these models are best thought of as testing the incremental information of both the indicator <u>and</u> real import prices against the AR benchmark.

Overall, then, these results suggest that labour market indicators may in principle be extremely useful to monetary policy makers in forecasting inflation over one year ahead. However, since these results relate to in-sample correlations, they do not offer much guidance on how useful labour market indicators are in real time. We have already mentioned that some of the relationships appear to be unstable and, of course, where our indicators are gap-based there is the additional problem that the estimated trend is based on full-sample information which would not be available *ex ante*. We return to these issues below by examining the out-of-sample forecasting performance of the indicators. Given the results from the in-sample tests, we focus only on the results for forecasting the change in one year ahead inflation.

**Table 5.1.1 – Do labour market indicators predict changes in DGI-RPIX inflation?**

| | Sample: 1973:4-1999:2 | | Sample: 1985:1-1999:2 | |
|---|---|---|---|---|
| Indicator | 1-quarter | 1-year | 1-quarter | 1-year |
| UR | 0.315 | 0.000** | 0.928 | 0.002** |
| LUR | 0.000** | 0.000** | 0.024* | 0.003** |
| CCR | 0.342 | 0.000** | 0.857 | 0.004** |
| STUR | 0.000** | 0.000** | 0.026* | 0.000** |
| MUR | 0.338 | 0.000** | 0.834 | 0.004** |
| UIR | 0.040* | 0.000** | 0.364 | 0.001** |
| UOR | 0.000** | 0.000** | 0.124 | 0.203 |
| NER | 0.344 | 0.001** | 0.644 | 0.008** |
| WNER | 0.271 | 0.003** | 0.551 | 0.008** |
| LJOBS | 0.384 | 0.001** | 0.703 | 0.004** |
| VU | 0.001** | 0.000** | 0.125 | 0.081 |
| VIU | 0.000** | 0.000** | 0.108 | 0.001** |
| VUI | 0.043* | 0.000** | 0.219 | 0.011* |
| SKILL | 0.001** | 0.000** | 0.367 | 0.084 |
| LSXPUB | 0.005** | 0.001** | 0.025* | 0.178 |
| LS | 0.002** | 0.000** | 0.010* | 0.044* |
| DUR | 0.037* | 0.000** | 0.167 | 0.000** |
| DLUR | 0.063 | 0.000** | 0.320 | 0.000** |
| DCCR | 0.030* | 0.000** | 0.237 | 0.000** |
| DSTUR | 0.019* | 0.000** | 0.404 | 0.000** |
| DMUR | 0.021* | 0.000** | 0.164 | 0.000** |
| DUIR | 0.046* | 0.021* | 0.021* | 0.004** |
| DUOR | 0.021* | 0.001** | 0.248 | 0.345 |
| DNER | 0.050 | 0.000** | 0.165 | 0.000** |
| DWNER | 0.041* | 0.000** | 0.171 | 0.000** |
| DLJOBS | 0.016* | 0.000** | 0.041* | 0.000** |
| DVU | 0.055 | 0.000** | 0.049* | 0.021* |
| DVIU | 0.000** | 0.000** | 0.446 | 0.000** |
| DVUI | 0.084 | 0.000** | 0.044* | 0.001** |
| DSKILL | 0.036* | 0.000** | 0.130 | 0.048* |

Notes:
Table reports p-value from F-test using HAC-corrected standard errors that $\gamma(L) = 0$ in regression:
$\pi^h_{t+h} - \pi_t = \alpha + \beta(L)\,\Delta\pi_t + \gamma(L)\,I_t + \eta(L)\,z_t + \varepsilon_{t+h}$
**/* indicates statistical significance at the 1%/5% level.
For variable definitions see Table 3.1 or Annex A.
Full-sample equations for indicators based on VU, VIU, VUI and SKILL are estimated over the period 1975:1-1999:2.

**Table 5.1.2 – Do labour indicators predict changes in RPIX inflation?**

| | Sample: 1974:1-1999:2 | | Sample: 1985:1-1999:2 | |
|---|---|---|---|---|
| Indicator | 1-quarter | 1-year | 1-quarter | 1-year |
| UR | 0.023* | 0.000** | 0.060 | 0.000** |
| LUR | 0.000** | 0.000** | 0.030* | 0.000** |
| CCR | 0.032* | 0.000** | 0.084 | 0.000** |
| STUR | 0.016* | 0.000** | 0.062 | 0.000** |
| MUR | 0.025* | 0.001** | 0.060 | 0.000** |
| UIR | 0.032* | 0.004** | 0.025* | 0.002** |
| UOR | 0.000** | 0.000** | 0.083 | 0.048* |
| NER | 0.044* | 0.003** | 0.036* | 0.000** |
| WNER | 0.034* | 0.018* | 0.012* | 0.001** |
| LJOBS | 0.035* | 0.006** | 0.054 | 0.000** |
| VU | 0.000** | 0.000** | 0.006** | 0.000** |
| VIU | 0.000** | 0.000** | 0.000** | 0.000** |
| VUI | 0.001** | 0.000** | 0.002** | 0.000** |
| SKILL | 0.000** | 0.000** | 0.001** | 0.000** |
| LSXPUB | 0.471 | 0.001** | 0.264 | 0.029* |
| LS | 0.063 | 0.000** | 0.016* | 0.002** |
| DUR | 0.042* | 0.000** | 0.000** | 0.000** |
| DLUR | 0.035* | 0.000** | 0.000** | 0.000** |
| DCCR | 0.078 | 0.000** | 0.068 | 0.000** |
| DSTUR | 0.086 | 0.008** | 0.685 | 0.000** |
| DMUR | 0.043* | 0.000** | 0.060 | 0.000** |
| DUIR | 0.150 | 0.142 | 0.236 | 0.004** |
| DUOR | 0.076 | 0.000** | 0.200 | 0.001** |
| DNER | 0.096 | 0.000** | 0.013* | 0.000** |
| DWNER | 0.189 | 0.003** | 0.184 | 0.000** |
| DLJOBS | 0.037* | 0.001** | 0.003** | 0.000** |
| DVU | 0.323 | 0.000** | 0.132 | 0.002** |
| DVIU | 0.000** | 0.000** | 0.015* | 0.000** |
| DVUI | 0.571 | 0.000** | 0.362 | 0.000** |
| DSKILL | 0.007** | 0.000** | 0.296 | 0.002** |

Notes: Table reports p-value from F-test using HAC-corrected standard errors that $\gamma(L) = 0$ in regression:
$\pi^h_{t+h} - \pi_t = \alpha + \beta\ (L)\ \Delta\ \pi_t + \gamma(L)\ I_t + \eta(L)\ z_t\ + \varepsilon_{t+h}$
**/* indicates statistical significance at the 1%/5% level.
For variable definitions see Table 3.1 or Annex A.
Full-sample equations for indicators based on VU, VIU, VUI and SKILL are estimated over the period 1975:1-1999:2.

**Table 5.1.3 – Do labour indicators predict changes in AEI inflation?**

| | Sample: 1974:1-1999:2 | | Sample: 1985:1-1999:2 | |
|---|---|---|---|---|
| Indicator | 1-quarter | 1-year | 1-quarter | 1-year |
| UR | 0.001** | 0.000** | 0.052 | 0.001** |
| LUR | 0.001** | 0.000** | 0.046* | 0.000** |
| CCR | 0.004** | 0.003** | 0.023* | 0.001** |
| STUR | 0.012* | 0.001** | 0.318 | 0.009** |
| MUR | 0.075 | 0.001** | 0.308 | 0.002** |
| UIR | 0.014* | 0.015* | 0.070 | 0.216 |
| UOR | 0.000** | 0.000** | 0.251 | 0.000** |
| NER | 0.002* | 0.002** | 0.079 | 0.000** |
| WNER | 0.139 | 0.033* | 0.137 | 0.000** |
| LJOBS | 0.082 | 0.007** | 0.336 | 0.000** |
| VU | 0.000** | 0.000** | 0.246 | 0.000** |
| VIU | 0.000** | 0.000** | 0.254 | 0.000** |
| VUI | 0.000** | 0.000** | 0.052 | 0.000** |
| SKILL | 0.000** | 0.000** | 0.029* | 0.194 |
| LSXPUB | 0.024* | 0.015* | 0.046* | 0.001** |
| LS | 0.005** | 0.001** | 0.003** | 0.000** |
| DUR | 0.003** | 0.000** | 0.005** | 0.000** |
| DLUR | 0.000** | 0.000** | 0.015* | 0.000** |
| DCCR | 0.011* | 0.000** | 0.004** | 0.000** |
| DSTUR | 0.055 | 0.001** | 0.068 | 0.000** |
| DMUR | 0.016* | 0.000** | 0.004** | 0.000** |
| DUIR | 0.402 | 0.447 | 0.004** | 0.000** |
| DUOR | 0.000** | 0.000** | 0.059 | 0.001** |
| DNER | 0.002** | 0.000** | 0.004** | 0.000** |
| DWNER | 0.004** | 0.003** | 0.001** | 0.000** |
| DLJOBS | 0.021* | 0.001** | 0.002** | 0.000** |
| DVU | 0.000** | 0.000** | 0.001** | 0.002** |
| DVIU | 0.000** | 0.000** | 0.014* | 0.000** |
| DVUI | 0.000** | 0.000** | 0.001** | 0.000** |
| DSKILL | 0.001** | 0.000** | 0.002** | 0.000** |

Notes: Table reports p-value from F-test using HAC-corrected standard errors that $\gamma(L) = 0$ in regression:
$\pi^h_{t+h} - \pi_t = \alpha + \beta\,(L)\,\Delta\,\pi_t + \gamma(L)\,I_t + \eta(L)\,z_t\; + \varepsilon_{t+h}$
**/* indicates statistical significance at the 1%/5% level.
For variable definitions see Table 3.1 or Annex A.
Full-sample equations for indicators based on VU, VIU, VUI and SKILL are estimated over the period 1975:1-1999:2.

### 5.2 *Out-of-sample test results*

#### 5.2.1 *Recursive forecast tests*

The full set of out-of-sample forecast results from the recursive models – which include relative MSE and $\lambda$ statistics for each indicator model for each inflation measure over 1985 Q1 to 2000 Q2, as well as for the three subperiods – is contained in Annex C in Tables C.2.1, C.2.2 and C.2.3. For convenience, Table 5.2.1 provides a ranking of the best and worst-performing individual indicators, according to the size of the root mean squared errors (RMSEs) of their forecasts, while Table 5.2.2 summarises the overall forecasting performance of the indicators relative to a naive random walk model (ie a no change forecast), an AR model and, for RPIX and AEI only, an 'import price-augmented' model that includes lags of both the inflation measure and of real import price inflation.(19) Table 5.2.2 also illustrates the relative MSEs obtained from averaging the MSEs for each indicator, as well as from combination forecasts based on the mean, median and 10% trimmed mean of the individual indicator model forecasts.

As can be seen from Tables 5.2.1 and 5.2.2, the performance of the different indicator models in forecasting changes in inflation varies considerably across sample periods and inflation measures and is quite poor overall in absolute terms. Taking a simple average over the 30 models over the 1985-2000 period produces RMSEs of 3.1% (DGI-RPIX), 2.1% (RPIX) and 2.1% (AEI), which compares with average annual inflation rates across this period of 4.9%, 4.0% and 6.2% respectively.(20) However, since these models are clearly incomplete, being bi-variate or, at most, tri-variate (in the case of the RPIX and AEI models), our interest is more in how they perform relative to one another and relative to the benchmark models, rather than their absolute forecasting performance *per se*.

One point that emerges from the rankings in Table 5.2.1 is that there is no single indicator model that always outperforms the others across all measures of inflation and in all sample periods. That said, there are clearly some indicator models that appear more consistently among either the best or worst-performing forecasts. Taking a simple ranking across all three inflation measures over the full sample suggests that the three models with the lowest forecast errors are those containing the ratio of new vacancies to the unemployment stock (VIU), the unemployment outflow rate (UOR) and the ratio of vacancies to unemployment (VU). Interestingly, given the standard specification of the Phillips curve in terms of the unemployment rate, the three indicator

(19) As distinct from the AR benchmark model, which only includes lags of the inflation measure itself.
(20) Annual inflation rates are calculated from averaging the year-on-year log changes in each measure.

models with the highest RMSEs on average are the ones with the male unemployment rate (MUR), the LFS unemployment rate (UR) and the claimant count unemployment rate (CCR).

As shown in Table 5.2.2, in relative terms the indicator models do best overall in forecasting movements in DGI-RPIX inflation, where all but two have lower RMSEs than the random walk model over the full-sample period and more than half outperform the AR benchmark. However, as is shown in Annex C, in only a handful of cases are the relative MSEs of the indicators statistically significant, ie it is difficult to reject the hypothesis that the indicator models are no better than the AR benchmark. In the case of the RPIX and AEI results, the indicator models do rather less well. In the case of the RPIX results, most of the indicator models outperform the random walk model over the full sample, but only three outperform the AR benchmark, and none of these results are statistically significant in terms of the relative MSE. In the case of the AEI, less than half the labour indicator models outperform the random walk model and five outperform the AR benchmark over the full sample, but again none of these results are statistically significant.

It needs to be borne in mind, however, that the RPIX and AEI models include terms in real import price inflation, so the relative MSE comparisons refer to the incremental information obtained from the relevant labour market indicator *and* terms in real import price inflation. Surprisingly, a larger number of the indicator models (at least for RPIX) have *lower* forecast errors relative to the import price augmented inflation model benchmark, because the latter tends to produce worse out-of-sample forecasts than the AR model. This presumably reflects the fact that adding import prices leads to overfitting and greater model instability.[21] (We found, however, that excluding real import price inflation from the indicator models for RPIX and AEI did not systematically lead to either better or worse out-of-sample forecasts.)

The forecast-encompassing tests (reported in Annex C) tell a broadly similar story to comparisons based on relative RMSEs in terms of the ranking of different indicators, though they suggest a lot more indicators can add information to out-of-sample forecasts. Indeed, a general finding of the encompassing tests is that indicators may add incremental information to forecasts from the AR benchmark model (ie have $\lambda$ coefficients that are positive and statistically significant) even when their RMSEs are higher. Obviously this is not necessarily contradictory because the two types of test are slightly different. We place more emphasis on the relative size

[21] The finding that adding information leads to worse forecasting performance through inducing instability is consistent with other literature on leading indicators (see eg Stock and Watson (1996), (1999)).

of the RMSEs in our analysis, however, because the standard errors from the encompassing regressions may be biased by the relatively small size of the sample period.

Finally, it is perhaps worth commenting on the fact that the relative forecasting performance of the indicator models against the benchmark AR model varies substantially over the sample. Although the labour market indicator models have lower RMSEs post-1995, as might be expected given inflation was lower and less volatile, their incremental value against the AR benchmark over this period is significantly lower, ie their relative MSE statistics are almost without exception greater than unity and higher than in the full-sample case.(22) Indeed in forecasting changes in inflation over 1995-2000 only one indicator does better than the AR benchmark for each inflation measure. It is difficult to give a conclusive reason for this deterioration in forecasting performance. It seems plausible that it could be at least partly related to changes in the United Kingdom's monetary regime over the period (the move to inflation targeting in October 1992 and the granting of operational independence to the Bank of England in May 1997), which may have made the authorities more forward-looking and so more likely to offset incipient inflationary pressures signalled by labour market variables. Another equally plausible (but not mutually exclusive) explanation is that the impact of structural reforms to the labour market may have led to a change in the relationship of labour market variables and inflation, which may have manifested following the early 1990s recession. Another possibility is that the pattern of shocks over this period (eg the sharp rise in the sterling exchange rate from August 1996) was unusual.

(22) Of course, this finding is consistent with other studies that find that UK wage and price equations break down in the mid-1990s.

### Table 5.2.1 – Labour market indicators ranked by root mean square error, according to recursive out-of-sample forecasts

| Inflation measure | Ranking low to high | 1985:1-1989:4 | 1990:1-1994:4 | 1995:1-2000:2 | 1985:1-2000:2 |
|---|---|---|---|---|---|
| DGI-RPIX | 1 | VUI (2.00) | DVUI (2.45) | DUIR (1.39) | VIU (2.09) |
| | 2 | VIU (2.07) | VIU (2.59) | SKILL (1.48) | UOR (2.20) |
| | 3 | UOR (2.09) | DVIU (2.75) | VU (1.50) | VU (2.28) |
| | 4 | VU (2.10) | DNER (2.78) | VIU (1.52) | DVIU (2.58) |
| | 5 | SKILL (2.23) | DCCR (2.79) | UOR (1.56) | DVU (2.59) |
| | 26 | DLUR (3.89) | NER (4.55) | DLUR (2.54) | LJOBS (3.72) |
| | 27 | WNER (4.17) | LJOBS (4.88) | UR (2.61) | UR (4.14) |
| | 28 | UR (5.09) | CCR (5.24) | CCR (2.78) | WNER (4.26) |
| | 29 | MUR (5.10) | MUR (5.37) | DVUI (2.90) | MUR (4.58) |
| | 30 | CCR (5.85) | WNER (5.69) | MUR (3.04) | CCR (4.76) |
| RPIX | 1 | UOR (1.43) | LSXPUB (1.35) | VU (0.47) | UOR (1.23) |
| | 2 | VU (1.52) | UOR (1.51) | UOR (0.60) | VU (1.27) |
| | 3 | VIU (1.54) | DVIU (1.51) | VIU (0.60) | VIU (1.30) |
| | 4 | DCCR (1.83) | VU (1.57) | DUOR (0.99) | DVIU (1.57) |
| | 5 | DMUR (1.84) | VIU (1.58) | DLJOBS (1.04) | DNER (1.69) |
| | 26 | CCR (3.27) | VUI (3.54) | NER (1.87) | WNER (2.99) |
| | 27 | LJOBS (3.27) | LJOBS (3.58) | VUI (1.92) | NER (3.03) |
| | 28 | WNER (3.37) | CCR (3.69) | UR (2.05) | MUR (3.07) |
| | 29 | NER (3.64) | WNER (3.72) | CCR (2.21) | CCR (3.10) |
| | 30 | UR (4.12) | MUR (4.11) | MUR (2.37) | UR (3.23) |
| AEI | 1 | VUI (0.99) | VIU (0.91) | VU (0.85) | VIU (1.05) |
| | 2 | VIU (1.14) | LSXPUB (1.12) | VIU (1.09) | UOR (1.26) |
| | 3 | UOR (1.31) | UOR (1.18) | DVU (1.14) | VU (1.27) |
| | 4 | DUOR (1.38) | NER (1.24) | DNER (1.23) | DVU (1.32) |
| | 5 | DVU (1.45) | DNER (1.26) | UOR (1.27) | DNER (1.35) |
| | 26 | DUIR (3.79) | DCCR (3.05) | LUR (1.93) | MUR (2.92) |
| | 27 | DUR (3.85) | UR (3.27) | DVUI (2.04) | DCCR (3.21) |
| | 28 | CCR (4.03) | CCR (3.81) | CCR (2.11) | DUIR (3.26) |
| | 29 | UR (4.25) | DUIR (3.98) | MUR (2.12) | UR (3.31) |
| | 30 | DCCR (4.48) | MUR (4.12) | UR (2.17) | CCR (3.39) |
| Memo items<br>RMSEs benchmark models: | | | | | |
| DGI-RPIX | Random walk | 4.69 | 5.46 | 2.86 | 4.43 |
| | AR model | 3.00 | 3.95 | 1.40 | 2.94 |
| RPIX | Random walk | 2.99 | 3.96 | 2.15 | 3.09 |
| | AR model | 1.28 | 1.89 | 0.59 | 1.34 |
| | Import price augmented | 2.31 | 1.80 | 1.47 | 1.88 |
| AEI | Random walk | 2.21 | 2.41 | 1.16 | 1.98 |
| | AR model | 1.51 | 1.82 | 0.91 | 1.45 |
| | Import price augmented | 1.54 | 1.45 | 1.57 | 1.52 |

Notes: Table shows for each inflation measure and time period the six indicators with the lowest and highest root mean squared errors (RMSEs), according to the out-of-sample forecast tests. RMSEs are shown in parentheses.

**Table 5.2.2 – Labour market indicators summary performance measures, based on recursive out-of-sample forecasts**

| Inflation measure | | 1985:1-1989:4 | 1990:1-1994:4 | 1995:1-2000:2 | 1985:1-2000:2 |
|---|---|---|---|---|---|
| DGI-RPIX | No (%) of indicators with lower RMSE than: | | | | |
| | Random walk model | 27 (90%) | 29 (97%) | 28 (93%) | 28 (93%) |
| | AR model | 10 (33%) | 20 (67%) | 1 (3%) | 17 (57%) |
| | Average indicator Relative MSE | 1.23 | 0.82 | 2.18 | 1.09 |
| | Combined Forecast Relative MSEs: | | | | |
| | MEAN | 0.88 | 0.48 | 1.36 | 0.68 |
| | TRIM MEAN | 0.87 | 0.47 | 1.33 | 0.68 |
| | MEDIAN | 0.89 | 0.45 | 1.26 | 0.66 |
| RPIX | No (%) of indicators with lower RMSE than: | | | | |
| | Random walk model | 24 (80%) | 29 (97%) | 28 (93%) | 28 (93%) |
| | AR model | 0 (0%) | 9 (30%) | 1 (3%) | 3 (10%) |
| | Import price augmented | 15 (50%) | 8 (27%) | 19 (63%) | 11 (37%) |
| | Average indicator Relative MSE | 3.65 | 1.59 | 5.51 | 2.50 |
| | Combined Forecast Relative MSEs: | | | | |
| | MEAN | 2.30 | 1.00 | 3.50 | 1.55 |
| | TRIM MEAN | 2.26 | 0.99 | 3.51 | 1.54 |
| | MEDIAN | 2.06 | 0.97 | 3.47 | 1.46 |
| AEI | No (%) of indicators with lower RMSE than: | | | | |
| | Random walk model | 16 (53%) | 21 (70%) | 3 (10%) | 11 (37%) |
| | AR model | 5 (17%) | 13 (43%) | 1 (3%) | 5 (17%) |
| | Import price augmented | 5 (17%) | 8 (27%) | 18 (60%) | 5 (17%) |
| | Average indicator Relative MSE | 2.62 | 1.45 | 2.99 | 2.16 |
| | Combined Forecast RMSEs: | | | | |
| | MEAN | 1.11 | 0.56 | 1.82 | 0.93 |
| | TRIM MEAN | 1.04 | 0.52 | 1.83 | 0.89 |
| | MEDIAN | 0.88 | 0.55 | 1.97 | 0.87 |

Note: Relative MSE shows the mean squared error relative to the MSE from the benchmark AR model.

### *5.2.2 Rolling-window forecast tests*

The out-of-sample forecasting results from the models estimated using a rolling window are shown in Tables C.2.4, C.2.5 and C.2.6 in Annex C. As before, Table 5.2.3 provides a summary of the best and worst-performing individual indicators, while Table 5.2.4 contains various measures of the overall performance of the models.

The absolute forecasting performance of the rolling-window models is broadly similar to the recursive models, if anything marginally worse. For comparison, taking a simple average across the 30 rolling models over the full-sample period produces forecast RMSEs of 3.2% for DGI-RPIX, 2.3% for RPIX and 2.1% for AEI.

Many of the other features of the results are also broadly similar to those based on the recursive estimates. Like the results for the recursive models, the rolling models have lower forecast errors over the post-1995 period, but their performance against the AR benchmark model deteriorates markedly. Overall, the rolling labour market indicator models do slightly better in predicting movements in DGI-RPIX and RPIX out of sample than they do in predicting AEI movements. Over the full sample, nearly all of the indicator models for DGI-RPIX and RPIX (bar one and three respectively) have lower MSEs than the random walk model; whereas only 40% of the indicators do in the case of the AEI. Against the AR benchmark, the performance of the models is more uniform across different price/wage inflation measures: only a few of the indicator models have lower MSEs over the full sample and none of these results are statistically significant. Again the forecast-encompassing tests are more encouraging than the relative MSE statistics in suggesting a much larger number of indicator models are able to add value to the AR model forecasts of each inflation measure.

The rankings by RMSE suggest no single indicator consistently outperforms or underperforms the rest; indeed, correlation analysis of the indicator rankings shows that the performance of the rolling-window models is more variable than for the recursive models across different sample periods and for different measures of inflation. Bearing this in mind, taking a simple ranking across all three inflation measures over the full sample suggests that the three best forecasting models contain the change in the non-employment rate, the change in the LFS unemployment rate and the unemployment inflow rate. The worst-performing indicator models on the same basis are those with the LFS unemployment rate, the weighted non-employment rate and the claimant count rate.

### *5.2.3 Combination forecast results*

Although there is some similarity between the best and worst-performing indicators identified from both the rolling and recursive estimation results – eg the unemployment rate gap appears to be one of the worse indicators on both methods – the fact that the best indicators are different might make one wary of singling out a particular indicator as the best on the basis of the full set of results. This intuition is confirmed from simple correlations of the rankings obtained using the two estimation methods; eg over the full sample, the correlation ranges from 0.55 for RPIX, 0.38 for AEI and 0.32 for DGI-RPIX.

In this context, it is worth highlighting the fact that the combination forecasts generally perform more consistently relative to the individual indicators. For example, comparing across the three inflation measures and the three sub-periods, the median forecast performs among the six best individual indicators ranked in terms of RMSE in all nine cases for the rolling results. This pattern is also reflected to a large degree in the recursive results discussed in the previous section, where the median forecast lies among the six best individual indicators ranked in terms of RMSE in six out of nine cases – the worst of the median forecasts was ranked ninth compared to the 30 individual forecasts – though it needs to be borne in mind that the median forecasts are still dominated by the AR model in five out of the nine subperiods. So overall our results are consistent with the view that combining information across indicators may be a better strategy than relying on any individual indicator (in line with the findings of Stock and Watson (2001) discussed earlier).

**Table 5.2.3 – Labour market indicators ranked by root mean square error, according to rolling window out-of-sample forecasts**

| Inflation measure | Ranking low to high | 1985:1-1989:4 | 1990:1-1994:4 | 1995:1-2000:2 | 1985:1-2000:2 |
|---|---|---|---|---|---|
| DGI-RPIX | 1 | VUI (1.86) | DLUR (1.83) | UIR (1.52) | UIR (2.37) |
| | 2 | UOR (2.11) | DUR (1.98) | VUI (1.69) | STUR (2.48) |
| | 3 | STUR (2.16) | DVIU (2.22) | STUR (1.82) | DUR (2.62) |
| | 4 | VU (2.25) | DMUR (2.37) | SKILL (1.82) | DLJOBS (2.68) |
| | 5 | VIU (2.28) | DCCR (2.56) | DNER (1.92) | UOR (2.73) |
| | 26 | MUR (4.37) | VU (4.81) | LS (2.79) | NER (3.63) |
| | 27 | NER (4.40) | SKILL (5.26) | DMUR (2.86) | WNER (3.71) |
| | 28 | WNER (4.54) | VUI (5.47) | DUOR (3.56) | CCR (3.75) |
| | 29 | UR (4.55) | UR (6.57) | DVIU (3.90) | LUR (4.41) |
| | 30 | CCR (5.03) | LUR (6.63) | DVU (4.46) | UR (4.78) |
| RPIX | 1 | UOR (1.40) | DUR (1.20) | DNER (0.59) | DNER (1.28) |
| | 2 | VU (1.50) | DVIU (1.30) | DLJOBS (0.75) | DUR (1.49) |
| | 3 | VIU (1.54) | DNER (1.47) | DUR (0.85) | UIR (1.55) |
| | 4 | DNER (1.59) | DUIR (1.60) | LJOBS (0.92) | STUR (1.57) |
| | 5 | DUOR (1.65) | DVU (1.62) | UIR (0.99) | DUIR (1.73) |
| | 26 | UR (4.14) | SKILL (3.13) | DVU (2.20) | UR (2.97) |
| | 27 | NER (4.18) | VUI (3.85) | VU (2.28) | LSXPUB (3.03) |
| | 28 | DLUR (4.26) | DLJOBS (3.85) | UOR (2.39) | WNER (3.25) |
| | 29 | LSXPUB (4.56) | NER (4.29) | DUOR (2.52) | LJOBS (3.45) |
| | 30 | WNER (4.61) | LJOBS (4.79) | DVIU (2.86) | NER (3.50) |
| AEI | 1 | DVUI (1.29) | DNER (1.37) | DNER (0.95) | UOR (1.37) |
| | 2 | VIU (1.37) | UOR (1.46) | LS (1.02) | DSTUR (1.48) |
| | 3 | UOR (1.42) | DUR (1.46) | DLJOBS (1.02) | DVUI (1.52) |
| | 4 | DSTUR (1.46) | DVU (1.46) | DMUR (1.05) | DNER (1.56) |
| | 5 | VUI (1.52) | DLJOBS (1.72) | DLUR (1.09) | DUOR (1.59) |
| | 26 | UR (3.14) | LSXPUB (2.65) | UR (1.47) | UR (2.46) |
| | 27 | LS (3.25) | MUR (2.67) | LSXPUB (1.49) | LS (2.62) |
| | 28 | LSXPUB (3.74) | LUR (2.78) | MUR (1.55) | DUIR (2.74) |
| | 29 | DUIR (4.07) | VUI (3.10) | CCR (1.87) | LSXPUB (2.75) |
| | 30 | DSKILL (4.63) | LS (3.11) | DVU (2.19) | DSKILL (3.03) |
| <u>Memo item</u><br>RMSE benchmark models: | | | | | |
| DGI-RPIX | Random walk | 4.69 | 5.46 | 2.86 | 4.43 |
| | AR model | 3.00 | 3.39 | 1.56 | 2.73 |
| RPIX | Random walk | 2.99 | 3.96 | 2.15 | 3.09 |
| | AR model | 2.10 | 1.77 | 0.68 | 1.61 |
| | Import price augmented | 1.55 | 1.71 | 0.65 | 1.37 |
| AEI | Random walk | 2.21 | 2.41 | 1.16 | 1.98 |
| | AR model | 1.80 | 1.75 | 1.03 | 1.55 |
| | Import price augmented | 1.62 | 1.82 | 1.29 | 1.58 |

Notes: Table shows for each inflation measure and time period the six indicators with the lowest and highest root mean squared errors (RMSEs), according to the out-of-sample forecast tests. RMSEs are shown in parentheses.

**Table 5.2.4 – Labour market indicators summary performance measures, based on rolling out-of-sample forecasts**

| Inflation measure | | 1985:1-1989:4 | 1990:1-1994:4 | 1995:1-2000:2 | 1985:1-2000:2 |
|---|---|---|---|---|---|
| DGI-RPIX | No (%) of indicators with lower RMSE than: | | | | |
| | Random walk model | 29 (97%) | 27 (90%) | 26 (87%) | 29 (97%) |
| | AR model | 11 (37%) | 13 (43%) | 1 (3%) | 5 (17%) |
| | Average indicator Relative MSE | 1.19 | 1.16 | 2.37 | 1.38 |
| | Combined Forecast Relative MSEs: | | | | |
| | MEAN | 0.71 | 0.66 | 1.32 | 0.76 |
| | TRIM MEAN | 0.71 | 0.65 | 1.24 | 0.74 |
| | MEDIAN | 0.70 | 0.57 | 1.15 | 0.69 |
| RPIX | No (%) of indicators with lower RMSE than: | | | | |
| | Random walk model | 19 (63%) | 28 (93%) | 25 (83%) | 27 (90%) |
| | AR model | 3 (10%) | 7 (23%) | 1 (3%) | 1 (3%) |
| | Import price augmented | 12 (40%) | 8 (27%) | 1 (3%) | 4 (13%) |
| | Average indicator Relative MSE | 2.98 | 2.06 | 5.30 | 2.89 |
| | Combined Forecast Relative MSEs: | | | | |
| | MEAN | 1.48 | 0.83 | 1.83 | 1.18 |
| | TRIM MEAN | 1.44 | 0.82 | 1.72 | 1.15 |
| | MEDIAN | 0.99 | 0.76 | 1.23 | 0.90 |
| AEI | No (%) of indicators with lower RMSE than: | | | | |
| | Random walk model | 12 (40%) | 19 (63%) | 7 (23%) | 12 (40%) |
| | AR model | 6 (20%) | 6 (20%) | 3 (10%) | 3 (10%) |
| | Import price augmented | 6 (20%) | 8 (27%) | 13 (43%) | 4 (13%) |
| | Average indicator Relative MSE | 1.93 | 1.52 | 1.63 | 1.76 |
| | Combined Forecast RMSEs: | | | | |
| | MEAN | 0.80 | 0.92 | 0.98 | 0.88 |
| | TRIM MEAN | 0.76 | 0.91 | 1.00 | 0.86 |
| | MEDIAN | 0.71 | 0.89 | 1.10 | 0.84 |

Notes: Relative MSE shows the mean squared error relative to the MSE from the benchmark AR model.

### *5.3 Assessment*

As we have seen, the out-of-sample forecast results present a rather different picture from those based on in-sample estimation. While in sample most labour market indicators appear to be statistically significant in an inflation-forecasting equation, a much smaller number of labour market indicator models do better in forecasting inflation out of sample than a simple AR model containing lagged inflation, and virtually none do so in the period since 1995.

This contrast merits some discussion. Although part of the reason for the dichotomy relates to the problem of trend estimation, this is clearly not the only factor because the contrast between *ex ante* and *ex post* results also holds for the indicators that are based on differenced variables, as well as those based on gap estimates. It therefore seems more to do with model instability and overfitting. Pinning down the source of this instability is difficult in this framework, but clearly the reduced-form nature of the Phillips curve regressions makes them subject to structural changes and changes in the pattern of shocks. Some evidence on this is shown in Charts 5.3.1, 5.3.2 and 5.3.3, which show the evolution of the sum of the coefficients in the recursive unemployment gap models. There is clear evidence of instability in most of the coefficients over the period, which seems likely to be related to poor out-of-sample forecast performance.

As already highlighted, another prominent feature of the results is that the out-of-sample forecasting performance of the individual labour market indicator models relative to the benchmark models tends to vary with the chosen inflation measure, sample period and estimation method. However, one consistent result is that the unemployment rate gap (measured by either the LFS rate or the claimant count), the most commonly used measure of labour market tightness, does rather poorly across a range of specifications.

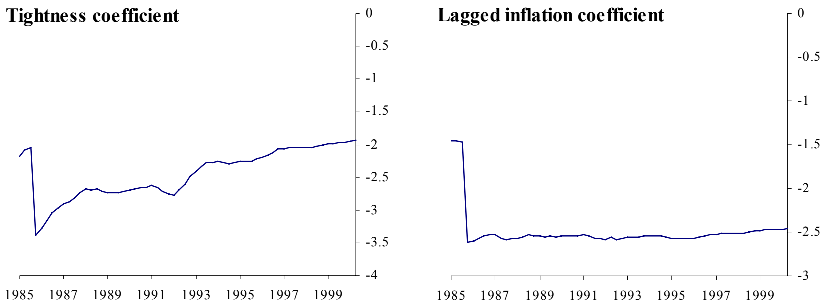
The failure of the unemployment Phillips curve relationship for the United Kingdom contrasts somewhat with findings for the United States and the euro area (see Stock and Watson (*op cit*) and Altimari (2001)), which tend to suggest that the simple Phillips curve does relatively well in forecasting inflation. In this case, however, it seems likely that a large part of the explanation for our results reflects the difficulties of estimating trend unemployment in real time, given the significant changes actual UK unemployment has exhibited over our sample period.[23] If we repeat the out-of-sample forecasting exercise for the unemployment gap model, using full-sample information to generate the gap, the model's RMSE falls substantially. In the case of the

[23] Although both studies cited refer to out-of-sample tests, unemployment in the United States has exhibited less variability than in the United Kingdom and the study for the euro area is based on a relatively short sample period.

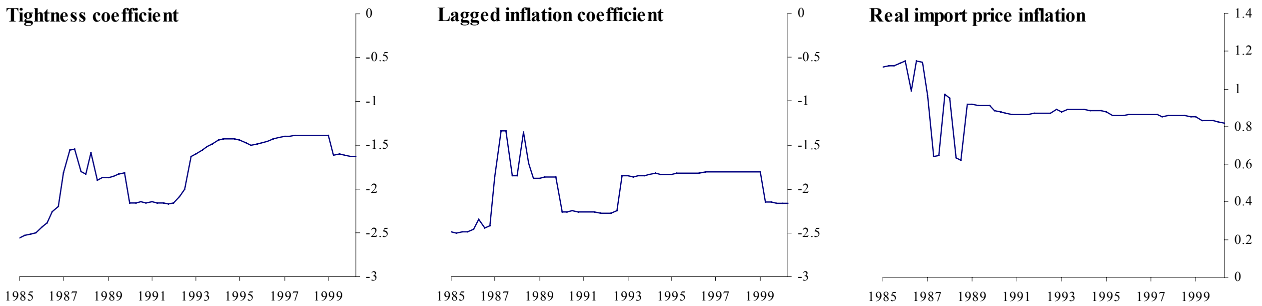
DGI-RPIX, the model does better than the AR model and, in the case of RPIX, it does as well as the lagged inflation model, though the improvement is less marked in the case of the AEI model.

One clear implication that emerges from this analysis is that the value of the gap models in forecasting inflation in real time depends critically on the methodology used to estimate the time-varying trend. We have followed the common practice of using the HP filter for this. Work on the respective merits of using different filters in (simulated) real-time situations would seem a useful area for future research.

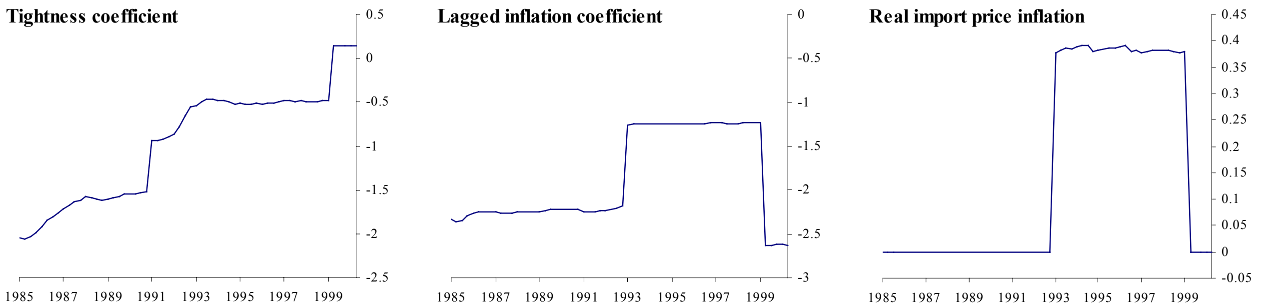
### Chart 5.3.1 – DGI-RPIX unemployment gap recursive model coefficients




### Chart 5.3.2 – RPIX unemployment gap recursive model coefficients




### Chart 5.3.3 – AEI unemployment gap recursive model coefficients



## 6. Conclusions

In this paper we have attempted to shed some light on which labour market indicators are more relevant when assessing the state of the labour market and any associated implications for inflationary pressure.

We did this by considering both the *ex post* performance of these indicators in predicting inflation using conventional in-sample Granger causality tests – and their performance *ex ante* – using simulated out-of-sample forecasting tests, based on both recursive and rolling-window estimation. These criteria give rather different conclusions. While in sample it is possible to find a relationship between most labour market indicators and future inflation, out of sample only a relatively small number of labour market indicator models do better than a simple autoregressive equation in forecasting inflation over the period since 1985, and virtually none do so over the period since 1995. Moreover, the best-performing indicators tend to be sensitive to the precise choice of inflation measure, sample period and estimation method, though there is some evidence that pooling across individual forecasts produces more reliable results. Although no individual indicators perform consistently well, one seemingly robust result is that the unemployment rate gap, the most commonly used measure of labour market tightness, does poorly across a range of specifications.

How do we explain the poor out-of-sample performance of the labour market indicator models? Part of the problem relates to the difficulty in identifying the relevant trends in the data. If we allow our HP trend estimate of equilibrium unemployment to be based on full-sample information, for example, we can substantially reduce our overall forecast error. However, this is not the whole story. We have noted the reduced-form nature of the analysis and it seems likely that a larger part of the problem relates to general model instability and consequent overfitting in sample. When the relationship between inflation and the tightness indicator changes over the forecast period, this then gets translated into forecast errors.

What lessons should be drawn from our analysis for policy-makers and others who monitor the labour market for signs of inflationary pressures? One response might be to conclude that, because the relationships between individual labour market indicators and inflation have proved unstable, we should place little weight on them. That would be a mistake in our view. If anything our results are probably best seen as supporting current practice: since no specific indicators are likely to be superior in all circumstances, the best approach by default is to try to take into account a wide variety of information in forming an assessment of the labour market.[24] This conclusion is reinforced by the fact that the simple combination forecasts we examine tend to perform more consistently relative to the individual indicator models. One challenge for future research is to develop methods that can efficiently synthesise the information contained in the large range of labour market data that is available.

[24] As King (1999) puts it: 'The MPC's analysis of the labour market is like the construction of a jigsaw puzzle. The pieces of data are assessed alongside each other in order to build up as clear a picture as possible. No single piece of data is interpreted in isolation. And no single piece of data is, in itself, decisive.'

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## Annex A – Data definitions

### (i) Price measures used to generate inflation data

### RPIX - Retail price index (excluding mortgage interest payments)

1975:1-2000:2: Spliced series combining current official RPIX series (1987=100) with previous series (1974=100)
Source: National Statistics (Series Codes: CHMK (current) and RYYW (previous))
1965:1-1974:4: Based on growth rates of General Index of Retail Prices
Source: National Statistics (Series Code: FRAG)

### AEI - Average Earnings Index

1965:1-2000:2: Seasonally adjusted Average Earnings Index
Source: National Statistics (Series Code: LNMQ)

### DGI-RPIX - Domestically-generated inflation (RPIX-based)

DGIRPIX = RPIX Inflation – Contribution of imported goods and services

Where Contribution of imported goods and services = Imports as % of total consumption * Import price inflation

*RPIX*: See above

*Imports as % of total consumption*:
1970:1-2000:2: Direct import share of consumption = (Imports of motor vehicles + Imports of other consumer goods)/ Total Household Final Expenditure (seasonally adjusted)
Source: National Statistics (Series Codes: BODK (Vehicle imports), BODL (Other consumer imports) and ABJQ (Household expenditure))

Direct import share is re-scaled to include indirect imported consumer items using the ratio of Total import share of consumption / Direct import share of consumption in 1990. (Total import share of consumption is derived from *Input / Output Tables* 1990)

### Import prices

1965:1-2000:2: Total nominal imports / Total real imports (Seasonally adjusted)
Source: National Statistics (Series Codes: IKBI (Nominal) and IKBL (Real))

### (ii) Labour market indicators

### UR = ILO-based unemployment rate (%)

1992:2-2000:2: LFS seasonally adjusted unemployment rate for all workers aged 16 and above
Source: National Statistics (Series Code: MGSX)
1967:1-1992:1: OECD standardised unemployment rate. Quarterly series from 1970 onwards. Interpolated from annual observations for 1967-1969.
Source: National Statistics (Series Code: GABF)

### CCR = Claimant count-based unemployment rate (%)

1965:1-2000:2: Seasonally adjusted claimant count unemployment rate
Source: National Statistics (Series Code: BCJE)

### STUR = Short-term unemployment rate

STUR = (Unemployed less than six months / (Stock of unemployed + employment stock))*100

*Unemployment stock*: See above

*Employment stock*: See above

*Unemployed less than six months:*
1999:1-2000:2: Based on claimant count unemployment up to six months (computerised claims only). Source: National Statistics (Series Code: GEYW). Rescaled to include manual claims.
1982:4-1998:4: Male and female claimant count unemployment up to six months
Source: National Statistics (Series Codes: BCNA (males) and BCNE (females))
1979:3-1982:3: Total claimant count unemployment up to six months
Source: *Employment Gazette,* various issues
1967:1-1979:2: Based on claimant count unemployment up to six months (Great Britain only), Source: *Employment Gazette*, various issues

Series is seasonally adjusted using X-12 program

## MUR = Male unemployment rate

1971:1-2000:2: Seasonally adjusted claimant count unemployment rate for males
Source: National Statistics (Series Code: DPAH)

## UIR = Unemployment inflow rate

Inflow rate = (Inflows into unemployment / Employment stock )*100

*Unemployment inflows*: See above

*Employment stock*: See above

## UOR = Unemployment exit rate

Outflow rate = (Outflow from unemployment / Stock of unemployed)*100

*Unemployment stock*: See above

*Unemployment outflows*:
1989:1-2000:2: Seasonally adjusted gross outflows from claimant count (Great Britain only). Source: National Statistics
1971:1-1988:4: Seasonally adjusted gross outflows from claimant count (Great Britain only). Source: Department for Education and Employment (based on data from *Employment Gazette*)

## NER = Non-employment rate (%)

NER = 100 - Employment Rate

*Employment rate*:
1992:2-2000:2: LFS seasonally adjusted employment rate for people of working age
Source: National Statistics (Series Code: MGSU)
1965:2-1992:1: Interpolated from annual estimates
Source: Bell I, 'Employment rates 1959-1999', *Labour Market Trends*, January 2000

## WNER = Weighted non-employment rate

$$WNONEMP = (\sum trans_i * nonemp_i) / POWA$$

where:

$nonemp_i$ = Number of individuals in category $i$ of non-employment
$trans_i$ = Transition probability of individuals in category $i$ moving from non-employment into employment
POWA = Population of Working Age

1984:2-2000:2: *$nonemp_i$ :* LFS Categories: Unemployed: less than 6 months, 6-12 months, more than 12 months, Inactive: not available to start work, discouraged workers, long-term sick, looking after family/home, students, other, doesn't want a job
Source: National Statistics (Series codes: YBWO, YBWR, YBWU, YCGD, YCFO, YCFR, YCFU, YCFX, YCGA, YBVZ)
(Figures before 1992 Q2 are interpolated from annual data)

$trans_I$ = Calculated from LFS Longitudinal data. Re-scaled based on unemployed less than 6 months as benchmark
Source: National Statistics

POWA = LFS Population of Working Age
Source: National Statistics (Series code: YBTF)
(Figures before 1992 Q2 are interpolated from annual data)

1965:2-1984:1: Based on quarterly changes in NONEMP (See above)

## JOBS = Employment

1967:2-2000:2: Total seasonally adjusted workforce jobs. Quarterly series from 1978 onwards. Interpolated from annual observations for 1967-1977
Source: National Statistics (Series Code: DYDC)

## VU = Stock of vacancies / Stock of unemployed

*Stock of unfilled vacancies:*
1980:1-2000:2: Seasonally adjusted stock of unfilled vacancies in Jobcentres (Great Britain only)
Source: National Statistics (Series Codes: BCQL (unfilled vacancies), DRYV (new vacancies))
1971:4-1979:4: Seasonally adjusted stock of unfilled vacancies in Jobcentres (Great Britain only)
Source: Department for Education and Employment (based on data from *Employment Gazette*)

*Unemployment stock:*
1971:1-2000:2: Stock of seasonally adjusted claimant count unemployment
Source: National Statistics (Series Code: BCJD)

## VIU = New vacancies / Stock of unemployed

*Vacancies inflows:*
1980:1-2000:2: Seasonally adjusted stock of new vacancies in Jobcentres (Great Britain only)
Source: National Statistics (Series Codes: BCQL (unfilled vacancies), DRYV (new vacancies))
1971:4-1979:4: Seasonally adjusted new vacancies in Jobcentres (Great Britain only)
Source: Department for Education and Employment (based on data from *Employment Gazette*)

*Stock of unfilled vacancies:*
See above.

## VUI = Stock of vacancies / Inflows into unemployment

*Stock of unfilled vacancies:*
See above.

*Unemployment inflows*:
1989:1-2000:2: Seasonally adjusted gross inflows into claimant count (Great Britain only). Source: National Statistics
1971:1-1988:4: Seasonally adjusted gross inflows into claimant count (Great Britain only). Source: Department for Education and Employment (based on data from *Employment Gazette*)

## SKILL = Skill shortages (%)

1971:4-2000:2: Net balance of responses to question 'Are shortages of skilled labour likely to limit your output over the next four months?' Source: CBI *Industrial Trends* Survey

## LS = Labour share of income adjusted for self-employment

LS = Labour income (incl. self-employment income) / Total Income

*Labour income (incl. self-employment income):*
1965:1-2000:2: Compensation of employees * ((employees + self employed)/employees)
Source: National Statistics (Series Codes: HAEA (Compensation of employees), BCAJ (employees) and DYZN (self employed)). Quarterly series for employees and self-employed from 1978 onwards. Interpolated from annual observations for 1965-1977.

*Total Income:*
1965:1-2000:2: Seasonally adjusted Gross Value Added at basic prices
Source: National Statistics (Series Code: ABML)

## LSXPUB = Labour share of income adjusted for self-employment and excluding the public sector

LSBJN = Labour income (incl. self-employment income – labour income paid by govt )/(Total Income – govt component)

*Labour income (incl. self-employment income – labour income paid by govt):*
1965:1-2000:2: ((Compensation of employees - Compensation paid by govt) * ((employees + self employed)/employees)
Where Compensation paid by govt = Compensation of employees paid by general government. Source: National Statistics (Series Code:NMXS)

*Government component of Total Income:*
1998:1-2000:2: Based on growth rate of General Govt Compensation of Employees + General Government Gross Operating Surplus
Source: National Statistics (Series Codes: NMXS and NMXV)
1987:1-1997:4: General Govt Gross Value Added
Source: National Statistics (Series Code: NMXN)
1965:1-1986:4: As for 1998:1-2000:2

## Annex B – Unit root tests

| Series | | $t_{ct}$ | $t_c$ | $\phi_3$ | Conclusion |
|---|---|---|---|---|---|
| RPI excluding mortgage interest payments | RPIX | -1.44 | -1.95 | 2.39 | I(2) / I(1) |
| Domestically generated inflation (DGI) - RPIX | DGI-RPIX | -1.43 | -2.65 | 3.70 | I(2) / I(1) |
| Average Earnings Index | AEI | 0.28 | -2.42 | 3.20 | I(2) / I(1) |
| LFS unemployment rate | UR | -1.93 | -2.13 | 2.33 | I(1) |
| Log of LFS unemployment rate | LUR | -1.73 | -2.07 | 2.19 | I(1) |
| Claimant count unemployment rate | CCR | -2.02 | -2.24 | 2.62 | I(1) |
| Short-term unemployment rate | STUR | -1.69 | -2.02 | 2.07 | I(1) |
| Male unemployment rate | MUR | -1.18 | -1.65 | 1.37 | I(1) |
| Unemployment inflow rate | UIR | -2.12 | -1.69 | 2.42 | I(1) |
| Unemployment outflow rate | UOR | -1.16 | -1.87 | 1.78 | I(1) |
| Non-employment rate | NER | -3.21 | -3.29* | 5.45 | I(1) / I(0) |
| Weighted non-employment rate | WNER | -1.66 | -1.81 | 2.09 | I(1) |
| Log of workforce jobs | LJOBS | -3.50* | -1.83 | 6.18 | I(1)/ I(0) |
| Ratio of vacancies to unemployment | VU | -3.21 | -3.17* | 5.29 | I(1)/ I(0) |
| Ratio of new vacancies to the stock of unemployment | VIU | -2.89 | -2.73 | 4.37 | I(1) |
| Ratio of vacancies to unemployment inflows | VUI | -1.79 | -1.49 | 2.00 | I(1) |
| CBI measure of skill shortages | SKILL | -2.77 | -2.53 | 3.84 | I(1) |
| Labour share adjusted for self-employment | LS | -3.74* | -3.77* | 7.00* | I(0) |
| Labour share adjusted for self-employment and excluding the public sector | LSXPUB | -2.92 | -3.09* | 4.80 | I(1) / I(0) |

Critical values for t-tests from Davidson and MacKinnon (1993). Critical values for F-test from Maddala and Kim (1998). $\Phi_3$ = Joint F-test of unit root and insignificant trend.

Lags lengths for ADF tests were chosen by minimising the Schwarz Information Criterion.

*- Reject H0 at 5%.

## Annex C – Out-of-sample forecast test results

### Table C.2.1 – Forecasting performance of recursive models of DGI-RPIX inflation relative to AR benchmark

| | 1985:1-1989:4 | | 1990:1-1994:4 | | 1995:1-2000:2 | | 1985:1-2000:2 | |
|---|---|---|---|---|---|---|---|---|
| Variable | Rel. MSE | λ | Rel. MSE | λ | Rel. MSE | λ | Rel. MSE | λ |
| AR baseline (% RMSE) | 3.00 | | 3.95 | | 1.40 | | 2.94 | |
| No change | 2.45 | 0.04 | 1.91 | 0.13 | 4.18 | 0.13 | 2.27 | 0.10 |
| | *(0.7)* | *(0.3)* | *(1.1)* | *(0.9)* | *(1.0)* | *(1.6)* | *(1.2)* | *(1.0)* |
| Gap models | | | | | | | | |
| UR | 2.88 | 0.24 | 1.27 | 0.43 | 3.48 | 0.21 | 1.99 | 0.32 |
| | *(1.1)* | *(2.4)* | *(0.4)* | *(3.2)* | *(0.5)* | *(2.1)* | *(1.2)* | *(4.6)* |
| LUR | 1.22 | 0.43 | 0.56 | 0.68 | 2.15 | 0.27 | 0.91 | 0.53 |
| | *(0.5)* | *(3.3)* | *(1.6)* | *(4.2)* | *(0.8)* | *(2.0)* | *(0.3)* | *(5.6)* |
| CCR | 3.81 | 0.15 | 1.76 | 0.36 | 3.95 | 0.21 | 2.63 | 0.26 |
| | *(0.9)* | *(1.7)* | *(0.5)* | *(2.9)* | *(0.4)* | *(2.5)* | *(1.0)* | *(3.6)* |
| STUR | 0.85 | 0.55 | 1.04 | 0.49 | 1.75 | 0.34 | 1.04 | 0.49 |
| | *(0.4)* | *(3.7)* | *(0.1)* | *(3.2)* | *(0.5)* | *(2.4)* | *(0.1)* | *(4.7)* |
| MUR | 2.90 | 0.20 | 1.85 | 0.35 | 4.73 | 0.20 | 2.43 | 0.28 |
| | *(0.9)* | *(1.8)* | *(0.5)* | *(2.9)* | *(0.4)* | *(2.5)* | *(1.0)* | *(3.8)* |
| UIR | 1.39 | 0.34 | 0.69 | 0.65 | 1.43 | 0.36 | 0.99 | 0.51 |
| | *(0.4)* | *(1.3)* | *(1.2)* | *(4.1)* | *(0.5)* | *(2.0)* | *(0.1)* | *(3.5)* |
| UOR | 0.49 | 1.03 | 0.51 | 1.07 | 1.25 | 0.22 | 0.56 | 0.99 |
| | *(1.6)* | *(2.5)* | *(2.2)* | *(12.0)* | *(1.2)* | *(1.3)* | *(2.1)* | *(6.2)* |
| NER | 1.40 | 0.18 | 1.32 | 0.42 | 2.48 | 0.27 | 1.44 | 0.37 |
| | *(0.8)* | *(0.7)* | *(0.7)* | *(5.2)* | *(1.1)* | *(2.4)* | *(1.2)* | *(4.8)* |
| WNER | 1.94 | 0.11 | 2.08 | 0.30 | 2.98 | 0.18 | 2.10 | 0.26 |
| | *(0.9)* | *(0.9)* | *(0.7)* | *(3.9)* | *(0.6)* | *(1.8)* | *(1.0)* | *(3.8)* |
| LJOBS | 1.57 | 1.17 | 1.52 | 0.37 | 2.33 | 0.29 | 1.61 | 0.33 |
| | *(1.0)* | *(1.0)* | *(0.7)* | *(3.7)* | *(0.7)* | *(2.2)* | *(1.1)* | *(4.0)* |
| VU | 0.49 | 1.30 | 0.59 | 1.11 | 1.16 | 0.29 | 0.60 | 1.09 |
| | *(1.6)* | *(3.3)* | *(1.8)* | *(8.6)* | *(0.5)* | *(0.8)* | *(1.9)* | *(7.0)* |
| VIU | 0.48 | 1.16 | 0.43 | 1.27 | 1.18 | 0.32 | 0.51 | 1.13 |
| | *(1.6)* | *(2.9)* | *(2.5)* | *(9.0)* | *(0.6)* | *(1.2)* | *(2.2)* | *(7.1)* |
| VUI | 0.44 | 0.98 | 1.05 | 0.48 | 1.90 | 0.31 | 0.92 | 0.54 |
| | *(1.6)* | *(3.4)* | *(0.2)* | *(5.6)* | *(0.8)* | *(2.5)* | *(0.5)* | *(6.2)* |
| SKILL | 0.56 | 0.82 | 1.08 | 0.47 | 1.12 | 0.45 | 0.91 | 0.54 |
| | *(1.38)* | *(4.7)* | *(0.3)* | *(4.4)* | *(0.3)* | *(3.3)* | *(0.5)* | *(5.8)* |
| LSXPUB | 1.03 | 0.40 | 0.86 | 0.78 | 2.53 | -0.08 | 1.05 | 0.42 |
| | *(0.1)* | *(0.4)* | *(1.4)* | *(3.2)* | *(1.6)* | *(1.0)* | *(0.3)* | *(1.8)* |
| LS | 1.04 | 0.38 | 0.68 | 0.78 | 3.07 | -0.01 | 0.99 | 0.51 |
| | *(0.1)* | *(0.4)* | *(1.4)* | *(4.4)* | *(1.0)* | *(0.1)* | *(0.0)* | *(2.5)* |

## Table C.2.1 (cont.)

| Variable | 1985:1-1989:1 Rel. MSE | 1985:1-1989:1 λ | 1990:1-1994:4 Rel. MSE | 1990:1-1994:4 λ | 1995:1-2000:2 Rel. MSE | 1995:1-2000:2 λ | 1985:1-2000:2 Rel. MSE | 1985:1-2000:2 λ |
|---|---|---|---|---|---|---|---|---|
| Difference models | | | | | | | | |
| UR | 1.41 | 0.29 | 0.53 | 1.25 | 2.21 | 0.18 | 0.96 | 0.53 |
| | *(1.0)* | *(2.0)* | *(2.3)* | *(6.4)* | *(1.0)* | *(1.2)* | *(0.2)* | *(3.4)* |
| LUR | 1.68 | 0.22 | 0.53 | 1.34 | 3.29 | 0.09 | 1.14 | 0.41 |
| | *(0.7)* | *(1.1)* | *(2.3)* | *(5.5)* | *(0.5)* | *(0.4)* | *(0.4)* | *(2.4)* |
| CCR | 1.61 | 0.22 | 0.50 | 1.09 | 2.22 | 0.19 | 1.01 | 0.49 |
| | *(1.1)* | *(1.9)* | *(2.2)* | *(4.8)* | *(1.1)* | *(1.6)* | *(0.0)* | *(3.0)* |
| STUR | 1.50 | 0.14 | 1.01 | 0.48 | 2.32 | 0.20 | 1.28 | 0.24 |
| | *(0.9)* | *(0.9)* | *(0.0)* | *(1.1)* | *(0.7)* | *(1.0)* | *(1.3)* | *(1.9)* |
| MUR | 1.54 | 0.21 | 0.54 | 0.97 | 2.44 | 0.18 | 1.03 | 0.48 |
| | *(1.0)* | *(1.6)* | *(2.0)* | *(4.2)* | *(1.1)* | *(1.6)* | *(0.1)* | *(3.1)* |
| UIR | 0.99 | 0.54 | 0.91 | 0.94 | 0.99 | 0.52 | 0.94 | 0.74 |
| | *(0.1)* | *(1.2)* | *(0.9)* | *(2.2)* | *(0.0)* | *(1.1)* | *(0.7)* | *(2.4)* |
| UOR | 1.00 | 0.54 | 0.90 | 2.62 | 2.26 | -0.11 | 1.04 | 0.33 |
| | *(0.1)* | *(0.7)* | *(1.2)* | *(1.9)* | *(0.6)* | *(0.6)* | *(0.4)* | *(0.8)* |
| NER | 1.11 | 0.36 | 0.49 | 1.38 | 1.54 | 0.14 | 0.78 | 0.80 |
| | *(0.4)* | *(1.1)* | *(2.6)* | *(12.4)* | *(0.8)* | *(0.5)* | *(1.2)* | *(3.6)* |
| WNER | 1.14 | 0.38 | 0.73 | 0.73 | 1.92 | 0.08 | 0.96 | 0.53 |
| | *(0.4)* | *(1.4)* | *(1.2)* | *(5.2)* | *(1.2)* | *(0.5)* | *(0.2)* | *(3.5)* |
| LJOBS | 1.19 | 0.35 | 0.51 | 1.14 | 1.42 | 0.23 | 0.81 | 0.69 |
| | *(0.6)* | *(1.7)* | *(2.6)* | *(7.9)* | *(0.8)* | *(1.0)* | *(1.0)* | *(3.6)* |
| VU | 1.00 | 0.59 | 0.51 | 1.30 | 1.79 | -0.12 | 0.78 | 0.98 |
| | *(0.1)* | *(0.4)* | *(2.3)* | *(5.2)* | *(0.7)* | *(0.4)* | *(1.2)* | *(3.4)* |
| VIU | 1.00 | 0.46 | 0.48 | 1.44 | 1.93 | 0.06 | 0.77 | 0.95 |
| | *(0.0)* | *(0.4)* | *(2.2)* | *(4.4)* | *(0.5)* | *(0.2)* | *(1.1)* | *(2.6)* |
| VUI | 0.95 | 1.00 | 0.38 | 0.91 | 4.31 | 0.02 | 0.89 | 0.58 |
| | *(0.6)* | *(1.4)* | *(2.7)* | *(8.6)* | *(0.3)* | *(0.1)* | *(0.4)* | *(2.8)* |
| SKILL | 1.00 | -1.87 | 0.83 | 1.29 | 1.93 | 0.08 | 0.98 | 0.57 |
| | *(0.5)* | *(0.4)* | *(2.2)* | *(3.0)* | *(0.9)* | *(0.4)* | *(0.2)* | *(1.9)* |
| Combined forecasts | | | | | | | | |
| MEAN | 0.88 | 0.63 | 0.48 | 1.00 | 1.36 | 0.34 | 0.68 | 0.79 |
| | *(0.5)* | *(2.3)* | *(2.4)* | *(5.6)* | *(0.6)* | *(1.6)* | *(1.6)* | *(5.7)* |
| TRIM MEAN | 0.87 | 0.65 | 0.47 | 1.02 | 1.33 | 0.35 | 0.68 | 0.81 |
| | *(0.5)* | *(2.2)* | *(2.4)* | *(5.6)* | *(0.6)* | *(1.6)* | *(1.6)* | *(5.7)* |
| MEDIAN | 0.89 | 0.67 | 0.45 | 1.17 | 1.26 | 0.37 | 0.66 | 0.89 |
| | *(0.5)* | *(1.9)* | *(2.5)* | *(6.5)* | *(0.5)* | *(1.7)* | *(1.7)* | *(5.6)* |

Notes:
RMSE denotes the root mean squared error statistic.
Rel. MSE shows the mean squared error from each indicator relative to the MSE from the benchmark AR model
λ statistic is described in the text.
The numbers in parentheses are the associated t-ratios corrected for heteroscedasticity and autocorrelation, see Stock and Watson (1999). Note that in the case of Rel. MSE the null hypothesis is that this ratio equals one.
For variable definitions, see Table 3.1 or Annex A.

**Table C.2.2 – Forecasting performance of recursive models of RPIX inflation relative to AR benchmark**

| | 1985:1-1989:4 | | 1990:1-1994:4 | | 1995:1-2000:2 | | 1985:1-2000:2 | |
|---|---|---|---|---|---|---|---|---|
| Variable | Rel. MSE | λ | Rel. MSE | λ | Rel. MSE | λ | Rel. MSE | λ |
| AR baseline (% RMSE) | 1.28 | | 1.89 | | 0.59 | | 1.34 | |
| No change | 5.49 | 0.07 | 4.37 | -0.03 | 13.21 | 0.11 | 5.31 | 0.04 |
| | *(0.5)* | *(0.7)* | *(0.6)* | *(0.3)* | *(0.5)* | *(2.7)* | *(0.7)* | *(0.6)* |
| Import price Augmented | 3.27 | 0.08 | 0.91 | 0.55 | 6.19 | 0.09 | 1.96 | 0.23 |
| | *(0.8)* | *(0.6)* | *(0.2)* | *(2.3)* | *(0.4)* | *(1.5)* | *(1.3)* | *(2.1)* |
| Gap models | | | | | | | | |
| UR | 10.40 | 0.08 | 3.01 | 0.32 | 11.97 | 0.11 | 5.78 | 0.19 |
| | *(0.2)* | *(1.2)* | *(0.5)* | *(5.6)* | *(0.2)* | *(4.5)* | *(0.5)* | *(3.6)* |
| LUR | 4.16 | 0.18 | 1.19 | 0.47 | 6.33 | 0.17 | 2.41 | 0.32 |
| | *(0.5)* | *(3.3)* | *(0.4)* | *(7.3)* | *(0.4)* | *(6.4)* | *(1.0)* | *(5.5)* |
| CCR | 6.57 | 0.16 | 3.81 | 0.29 | 13.94 | 0.09 | 5.31 | 0.23 |
| | *(0.6)* | *(2.6)* | *(0.5)* | *(5.5)* | *(0.2)* | *(3.5)* | *(0.7)* | *(5.9)* |
| STUR | 2.71 | 0.26 | 1.70 | (0.4) | 6.94 | 0.16 | 2.36 | 0.32 |
| | *(0.6)* | *(5.6)* | *(0.8)* | *(6.5)* | *(0.4)* | *(4.0)* | *(1.2)* | *(6.9)* |
| MUR | 3.72 | 0.24 | 4.73 | 0.26 | 16.02 | 0.09 | 5.21 | 0.23 |
| | *(0.9)* | *(3.7)* | *(0.4)* | *(5.8)* | *(0.2)* | *(3.6)* | *(0.5)* | *(6.8)* |
| UIR | 2.56 | 0.25 | 1.60 | 0.40 | 7.44 | 0.12 | 2.28 | 0.32 |
| | *(0.9)* | *(2.7)* | *(0.7)* | *(5.2)* | *(0.6)* | *(2.6)* | *(1.3)* | *(5.5)* |
| UOR | 1.25 | 0.40 | 0.63 | 0.78 | 1.01 | 0.50 | 0.84 | 0.59 |
| | *(0.5)* | *(2.4)* | *(1.5)* | *(6.2)* | *(0.1)* | *(6.7)* | *(0.8)* | *(5.5)* |
| NER | 8.16 | 0.11 | 3.17 | 0.30 | 10.00 | 0.11 | 5.09 | 0.21 |
| | *(0.2)* | *(1.9)* | *(0.8)* | *(9.4)* | *(0.3)* | *(3.0)* | *(0.5)* | *(4.1)* |
| WNER | 6.98 | 0.12 | 3.86 | 0.26 | 6.68 | 0.13 | 4.96 | 0.20 |
| | *(0.2)* | *(2.5)* | *(0.4)* | *(5.7)* | *(0.7)* | *(3.1)* | *(0.4)* | *(5.4)* |
| LJOBS | 6.57 | 0.15 | 3.58 | 0.28 | 5.56 | 0.18 | 4.59 | 0.23 |
| | *(0.3)* | *(2.6)* | *(0.7)* | *(7.6)* | *(0.5)* | *(3.3)* | *(0.6)* | *(5.6)* |
| VU | 1.42 | 0.34 | 0.69 | 0.77 | 0.63 | 0.73 | 0.90 | 0.56 |
| | *(0.6)* | *(1.7)* | *(1.2)* | *(3.8)* | *(1.3)* | *(4.0)* | *(0.4)* | *(3.9)* |
| VIU | 1.45 | 0.37 | 0.70 | 0.62 | 1.02 | 0.49 | 0.94 | 0.52 |
| | *(0.9)* | *(3.3)* | *(1.2)* | *(8.7)* | *(0.1)* | *(4.6)* | *(0.3)* | *(7.6)* |
| VUI | 2.88 | 0.17 | 3.49 | 0.25 | 10.49 | 0.09 | 3.80 | 0.21 |
| | *(1.1)* | *(2.2)* | *(0.6)* | *(4.0)* | *(0.3)* | *(1.7)* | *(0.8)* | *(3.8)* |
| SKILL | 4.02 | 0.05 | 2.93 | 0.25 | 5.96 | 0.18 | 3.46 | 0.19 |
| | *(0.7)* | *(0.4)* | *(0.7)* | *(2.3)* | *(0.5)* | *(6.6)* | *(0.9)* | *(2.3)* |
| LSXPUB | 3.33 | 0.14 | 0.51 | 0.67 | 5.52 | 0.15 | 1.68 | 0.35 |
| | *(0.8)* | *(1.7)* | *(1.5)* | *(4.8)* | *(0.7)* | *(3.1)* | *(1.0)* | *(3.5)* |
| LS | 4.17 | 0.11 | 0.80 | 0.54 | 3.80 | 0.19 | 1.99 | 0.33 |
| | *(0.4)* | *(1.7)* | *(0.7)* | *(7.5)* | *(0.6)* | *(2.0)* | *(0.8)* | *(3.7)* |

## Table C.2.2 (cont.)

| | 1985:1-1989:1 | | 1990:1-1994:4 | | 1995:1-2000:2 | | 1985:1-2000:2 | |
|---|---|---|---|---|---|---|---|---|
| Variable | Rel. MSE | λ | Rel. MSE | λ | Rel. MSE | λ | Rel. MSE | λ |
| Difference models | | | | | | | | |
| UR | 2.95 | 0.26 | 0.91 | 0.53 | 5.01 | 0.16 | 1.78 | 0.36 |
| | *(1.0)* | *(5.3)* | *(0.2)* | *(4.1)* | *(0.5)* | *(3.3)* | *(1.2)* | *(4.9)* |
| LUR | 5.19 | 0.12 | 1.46 | 0.40 | 7.38 | 0.10 | 2.95 | 0.24 |
| | *(0.5)* | *(0.9)* | *(1.0)* | *(7.5)* | *(0.4)* | *(2.7)* | *(1.0)* | *(2.9)* |
| CCR | 2.06 | 0.31 | 1.04 | 0.49 | 5.05 | 0.16 | 1.62 | 0.38 |
| | *(1.2)* | *(3.1)* | *(0.1)* | *(4.4)* | *(0.4)* | *(3.0)* | *(1.1)* | *(5.0)* |
| STUR | 4.10 | 0.16 | 1.29 | 0.41 | 3.66 | 0.17 | 2.27 | 0.26 |
| | *(0.5)* | *(3.6)* | *(0.5)* | *(3.1)* | *(0.8)* | *(2.9)* | *(1.0)* | *(3.9)* |
| MUR | 2.07 | 0.30 | 1.16 | 0.47 | 4.73 | 0.17 | 1.67 | 0.38 |
| | *(0.8)* | *(2.6)* | *(0.3)* | *(4.9)* | *(0.4)* | *(3.2)* | *(1.1)* | *(5.3)* |
| UIR | 2.93 | 0.15 | 1.36 | 0.39 | 5.82 | 0.10 | 2.12 | 0.25 |
| | *(0.7)* | *(1.2)* | *(0.6)* | *(3.0)* | *(0.4)* | *(1.4)* | *(1.3)* | *(2.9)* |
| UOR | 2.61 | 0.12 | 1.03 | 0.49 | 2.76 | 0.25 | 1.61 | 0.30 |
| | *(0.9)* | *(1.1)* | *(0.1)* | *(2.6)* | *(0.7)* | *(3.8)* | *(1.2)* | *(2.8)* |
| NER | 2.36 | 0.26 | 0.99 | 0.50 | 3.90 | 0.17 | 1.59 | 0.38 |
| | *(0.8)* | *(3.0)* | *(0.0)* | *(4.9)* | *(0.9)* | *(3.1)* | *(1.1)* | *(4.9)* |
| WNER | 2.75 | 0.24 | 1.76 | 0.37 | 4.44 | 0.16 | 2.23 | 0.31 |
| | *(0.7)* | *(2.6)* | *(0.6)* | *(4.3)* | *(0.7)* | *(2.1)* | *(1.0)* | *(5.0)* |
| LJOBS | 2.65 | 0.22 | 1.08 | 0.48 | 3.11 | 0.24 | 1.68 | 0.36 |
| | *(0.8)* | *(2.2)* | *(0.2)* | *(4.3)* | *(1.2)* | *(6.6)* | *(1.2)* | *(4.4)* |
| VU | 5.83 | 0.03 | 0.84 | 0.56 | 4.01 | 0.10 | 2.51 | 0.22 |
| | *(0.5)* | *(0.5)* | *(0.4)* | *(3.3)* | *(0.6)* | *(1.5)* | *(0.8)* | *(2.1)* |
| VIU | 2.30 | 0.21 | 0.63 | 0.64 | 4.28 | 0.17 | 1.37 | 0.40 |
| | *(0.8)* | *(1.4)* | *(1.0)* | *(4.3)* | *(0.4)* | *(2.2)* | *(0.7)* | *(3.4)* |
| VUI | 4.94 | 0.07 | 1.84 | 0.39 | 7.57 | 0.02 | 3.14 | 0.25 |
| | *(0.5)* | *(1.1)* | *(1.0)* | *(7.7)* | *(0.6)* | *(0.3)* | *(1.1)* | *(3.7)* |
| SKILL | 3.75 | 0.06 | 1.03 | 0.48 | 5.94 | 0.08 | 2.16 | 0.21 |
| | *(0.7)* | *(0.5)* | *(0.1)* | *(2.8)* | *(0.4)* | *(1.4)* | *(1.2)* | *(2.1)* |
| Combined forecasts | | | | | | | | |
| MEAN | 2.30 | 0.26 | 1.00 | 0.50 | 3.50 | 0.22 | 1.55 | 0.39 |
| | *(0.7)* | *(0.5)* | *(0.0)* | *(2.8)* | *(0.6)* | *(1.4)* | *(1.1)* | *(2.1)* |
| TRIM MEAN | 2.26 | 0.26 | 0.99 | 0.50 | 3.51 | 0.22 | 1.54 | 0.39 |
| | *(0.7)* | *(3.2)* | *(0.0)* | *(5.9)* | *(0.6)* | *(3.4)* | *(1.1)* | *(5.6)* |
| MEDIAN | 2.06 | 0.28 | 0.97 | 0.51 | 3.47 | 0.22 | 1.46 | 0.40 |
| | *(0.8)* | *(3.4)* | *(0.1)* | *(5.1)* | *(0.5)* | *(3.1)* | *(1.0)* | *(5.4)* |

Notes:
RMSE denotes the root mean squared error statistic.
Rel. MSE shows the mean squared error from each indicator relative to the MSE from the benchmark AR model
λ statistic is described in the text.
The numbers in parentheses are the associated t-ratios corrected for heteroscedasticity and autocorrelation, see Stock and Watson (1999). Note that in the case of Rel. MSE the null hypothesis is that this ratio equals one.
For variable definitions, see Table 3.1 or Annex A.

**Table C.2.3 – Forecasting performance of recursive models of AEI inflation relative to AR benchmark**

| | 1985:1-1989:4 | | 1990:1-1994:4 | | 1995:1-2000:2 | | 1985:1-2000:2 | |
|---|---|---|---|---|---|---|---|---|
| Variable | Rel. MSE | λ | Rel. MSE | λ | Rel. MSE | λ | Rel. MSE | λ |
| AR baseline (% RMSE) | 1.51 | | 1.82 | | 0.91 | | 1.45 | |
| No change | 2.14 | -0.34 | 1.74 | -0.11 | 1.61 | -0.23 | 1.86 | -0.21 |
| | *(1.9)* | *(1.9)* | *(1.3)* | *(0.6)* | *(1.5)* | *(0.9)* | *(1.8)* | *(1.8)* |
| Import price Augmented | 1.03 | 0.48 | 0.63 | 0.78 | 2.98 | -0.15 | 1.10 | 0.44 |
| | *(0.1)* | *(2.5)* | *(1.1)* | *(2.5)* | *(0.6)* | *(0.6)* | *(0.3)* | *(2.5)* |
| Gap models | | | | | | | | |
| UR | 7.89 | 0.17 | 3.21 | 0.29 | 5.66 | 0.02 | 5.20 | 0.20 |
| | *(0.5)* | *(2.4)* | *(0.3)* | *(3.3)* | *(0.3)* | *(0.2)* | *(0.6)* | *(4.3)* |
| LUR | 1.73 | 0.36 | 0.82 | 0.54 | 4.49 | 0.10 | 1.65 | 0.38 |
| | *(1.0)* | *(3.0)* | *(0.6)* | *(7.6)* | *(0.4)* | *(0.9)* | *(1.0)* | *(4.7)* |
| CCR | 7.10 | 0.17 | 4.36 | 0.28 | 5.38 | 0.03 | 5.47 | 0.21 |
| | *(0.5)* | *(1.8)* | *(0.5)* | *(8.6)* | *(0.4)* | *(0.3)* | *(0.7)* | *(4.5)* |
| STUR | 2.57 | 0.32 | 1.55 | 0.41 | 2.56 | 0.23 | 2.05 | 0.35 |
| | *(0.9)* | *(3.7)* | *(0.4)* | *(4.2)* | *(0.5)* | *(1.4)* | *(1.0)* | *(6.1)* |
| MUR | 1.99 | 0.31 | 5.12 | 0.27 | 5.40 | 0.03 | 4.06 | 0.25 |
| | *(1.0)* | *(3.3)* | *(0.4)* | *(7.7)* | *(0.4)* | *(0.3)* | *(0.6)* | *(6.9)* |
| UIR | 3.26 | 0.22 | 1.58 | 0.40 | 3.83 | -0.04 | 2.48 | 0.28 |
| | *(0.4)* | *(1.6)* | *(0.6)* | *(4.1)* | *(0.6)* | *(0.3)* | *(0.7)* | *(3.0)* |
| UOR | 0.75 | 0.67 | 0.42 | 1.01 | 1.95 | 0.05 | 0.75 | 0.68 |
| | *(0.8)* | *(3.4)* | *(1.8)* | *(4.4)* | *(1.0)* | *(0.3)* | *(1.0)* | *(4.0)* |
| NER | 1.31 | 0.35 | 0.46 | 0.80 | 3.14 | 0.04 | 1.13 | 0.44 |
| | *(0.6)* | *(1.4)* | *(1.7)* | *(4.0)* | *(0.7)* | *(0.3)* | *(0.4)* | *(2.9)* |
| WNER | 3.47 | 0.14 | 0.53 | 0.76 | 2.95 | -0.09 | 1.90 | 0.26 |
| | *(0.4)* | *(1.1)* | *(1.4)* | *(3.8)* | *(0.7)* | *(0.4)* | *(0.6)* | *(1.9)* |
| LJOBS | 1.98 | 0.36 | 2.28 | 0.35 | 3.54 | 0.03 | 2.35 | 0.32 |
| | *(1.0)* | *(5.7)* | *(0.6)* | *(5.8)* | *(0.6)* | *(0.2)* | *(1.0)* | *(6.9)* |
| VU | 1.13 | 0.42 | 0.50 | 1.04 | 0.88 | 0.68 | 0.77 | 0.70 |
| | *(0.4)* | *(2.3)* | *(1.6)* | *(4.1)* | *(0.5)* | *(1.9)* | *(1.0)* | *(3.6)* |
| VIU | 0.57 | 0.78 | 0.25 | 0.86 | 1.44 | 0.23 | 0.53 | 0.76 |
| | *(1.1)* | *(4.0)* | *(2.4)* | *(10.4)* | *(0.7)* | *(1.0)* | *(1.8)* | *(7.9)* |
| VUI | 0.43 | 0.71 | 2.71 | 0.32 | 3.40 | 0.18 | 2.01 | 0.35 |
| | *(1.4)* | *(8.4)* | *(1.0)* | *(6.2)* | *(0.6)* | *(1.3)* | *(1.0)* | *(6.3)* |
| SKILL | 1.89 | 0.31 | 2.75 | 0.31 | 4.15 | -0.04 | 2.65 | 0.27 |
| | *(0.9)* | *(1.7)* | *(0.7)* | *(6.3)* | *(0.8)* | *(0.4)* | *(1.1)* | *(4.4)* |
| LSXPUB | 1.50 | 0.40 | 0.38 | 0.78 | 3.20 | -0.12 | 1.16 | 0.45 |
| | *(0.8)* | *(3.7)* | *(1.9)* | *(5.8)* | *(0.7)* | *(0.6)* | *(0.4)* | *(4.3)* |
| LS | 4.19 | 0.25 | 1.55 | 0.43 | 2.04 | 0.22 | 2.54 | 0.33 |
| | *(0.3)* | *(4.8)* | *(0.7)* | *(7.3)* | *(0.8)* | *(1.2)* | *(0.7)* | *(6.8)* |

**Table C.2.3 (cont.)**

| | 1985:1-1989:1 | | 1990:1-1994:4 | | 1995:1-2000:2 | | 1985:1-2000:2 | |
|---|---|---|---|---|---|---|---|---|
| Variable | Rel. MSE | λ | Rel. MSE | λ | Rel. MSE | λ | Rel. MSE | λ |
| Difference models | | | | | | | | |
| UR | 6.45 | 0.16 | 0.94 | 0.52 | 2.92 | 0.10 | 3.15 | 0.23 |
| | *(0.6)* | *(1.8)* | *(0.1)* | *(3.6)* | *(0.5)* | *(0.6)* | *(0.8)* | *(3.0)* |
| LUR | 4.28 | 0.18 | 2.30 | 0.21 | 4.42 | 0.15 | 3.29 | 0.19 |
| | *(0.6)* | *(1.5)* | *(0.6)* | *(1.3)* | *(0.5)* | *(1.3)* | *(0.9)* | *(2.2)* |
| CCR | 8.73 | 0.09 | 2.80 | 0.22 | 2.87 | 0.10 | 4.89 | 0.13 |
| | *(0.2)* | *(1.2)* | *(0.6)* | *(1.8)* | *(0.5)* | *(0.7)* | *(0.4)* | *(1.9)* |
| STUR | 4.05 | 0.24 | 1.70 | 0.37 | 2.71 | 0.22 | 2.66 | 0.28 |
| | *(0.6)* | *(2.9)* | *(0.8)* | *(3.4)* | *(0.6)* | *(1.6)* | *(1.0)* | *(4.3)* |
| MUR | 4.40 | 0.11 | 0.92 | 0.52 | 2.61 | 0.09 | 2.38 | 0.27 |
| | *(0.4)* | *(1.5)* | *(0.2)* | *(5.3)* | *(0.5)* | *(0.5)* | *(0.7)* | *(2.8)* |
| UIR | 6.26 | -0.01 | 4.77 | 0.18 | 2.95 | -0.02 | 5.04 | 0.10 |
| | *(0.2)* | *(0.1)* | *(0.2)* | *(2.0)* | *(0.6)* | *(0.8)* | *(0.3)* | *(1.5)* |
| UOR | 0.83 | 0.58 | 1.27 | 0.21 | 2.52 | 0.15 | 1.29 | 0.34 |
| | *(0.3)* | *(2.4)* | *(1.0)* | *(1.1)* | *(0.5)* | *(1.0)* | *(0.9)* | *(2.4)* |
| NER | 1.05 | 0.49 | 0.48 | 0.68 | 1.83 | 0.16 | 0.87 | 0.54 |
| | *(0.1)* | *(3.6)* | *(1.6)* | *(6.4)* | *(1.0)* | *(0.8)* | *(0.5)* | *(6.0)* |
| WNER | 3.00 | 0.26 | 1.26 | 0.45 | 2.96 | -0.06 | 2.11 | 0.31 |
| | *(0.8)* | *(2.7)* | *(0.6)* | *(6.4)* | *(0.8)* | *(0.3)* | *(1.3)* | *(4.7)* |
| LJOBS | 1.56 | 0.38 | 0.83 | 0.54 | 2.18 | -0.02 | 1.28 | 0.43 |
| | *(0.8)* | *(2.9)* | *(0.6)* | *(6.8)* | *(1.1)* | *(0.1)* | *(0.9)* | *(5.5)* |
| VU | 0.92 | 0.55 | 0.57 | 1.18 | 1.56 | 0.33 | 0.83 | 0.62 |
| | *(0.8)* | *(5.9)* | *(1.7)* | *(3.6)* | *(0.5)* | *(1.7)* | *(0.9)* | *(4.2)* |
| VIU | 1.29 | 0.43 | 0.93 | 0.54 | 2.32 | 0.23 | 1.25 | 0.42 |
| | *(0.5)* | *(4.2)* | *(0.2)* | *(2.7)* | *(0.8)* | *(1.5)* | *(0.8)* | *(4.7)* |
| VUI | 1.29 | 0.43 | 1.57 | 0.42 | 5.03 | 0.19 | 1.95 | 0.37 |
| | *(0.3)* | *(2.5)* | *(0.5)* | *(6.0)* | *(0.5)* | *(2.2)* | *(1.0)* | *(6.0)* |
| SKILL | 4.97 | 0.12 | 1.36 | 0.44 | 2.46 | 0.04 | 2.78 | 0.26 |
| | *(0.4)* | *(0.8)* | *(0.7)* | *(7.3)* | *(1.5)* | *(0.2)* | *(0.7)* | *(2.4)* |
| Combined forecasts | | | | | | | | |
| MEAN | 1.11 | 0.47 | 0.56 | 0.63 | 1.82 | 0.18 | 0.93 | 0.52 |
| | *(0.2)* | *(3.0)* | *(1.4)* | *(7.1)* | *(0.6)* | *(0.8)* | *(0.2)* | *(5.8)* |
| TRIM MEAN | 1.04 | 0.49 | 0.52 | 0.65 | 1.83 | 0.18 | 0.89 | 0.53 |
| | *(0.1)* | *(3.2)* | *(1.6)* | *(7.2)* | *(0.6)* | *(0.8)* | *(0.4)* | *(6.0)* |
| MEDIAN | 0.88 | 0.54 | 0.55 | 0.64 | 1.97 | 0.12 | 0.87 | 0.54 |
| | *(0.2)* | *(3.6)* | *(1.5)* | *(6.5)* | *(0.7)* | *(0.6)* | *(0.5)* | *(5.9)* |

Notes:
RMSE denotes the root mean squared error statistic.
Rel. MSE shows the mean squared error from each indicator relative to the MSE from the benchmark AR model
λ statistic is described in the text.
The numbers in parentheses are the associated t-ratios corrected for heteroscedasticity and autocorrelation, see Stock and Watson (1999). Note that in the case of Rel. MSE the null hypothesis is that this ratio equals one.
For variable definitions, see Table 3.1 or Annex A.

**Table C.2.4 – Forecasting performance of ten-year rolling-window models of DGI-RPIX inflation relative to AR benchmark**

| | 1985:1-1989:4 | | 1990:1-1994:4 | | 1995:1-2000:2 | | 1985:1-2000:2 | |
|---|---|---|---|---|---|---|---|---|
| Variable | Rel. MSE | λ | Rel. MSE | λ | Rel. MSE | λ | Rel. MSE | λ |
| AR baseline (% RMSE) | 3.00 | | 3.39 | | 1.56 | | 2.73 | |
| No change | 2.45 | 0.05 | 2.60 | -0.03 | 3.34 | 0.20 | 2.63 | 0.06 |
| | *(0.6)* | *(0.3)* | *(0.9)* | *(0.2)* | *(1.1)* | *(2.1)* | *(1.1)* | *(0.6)* |
| Gap models | | | | | | | | |
| UR | 2.31 | 0.32 | 3.76 | 0.20 | 2.56 | 0.20 | 3.06 | 0.24 |
| | *(0.9)* | *(4.4)* | *(0.4)* | *(2.4)* | *(0.6)* | *(1.7)* | *(0.6)* | *(3.6)* |
| LUR | 1.08 | 0.48 | 3.83 | 0.21 | 2.51 | 0.18 | 2.61 | 0.27 |
| | *(0.2)* | *(5.4)* | *(0.3)* | *(2.2)* | *(0.7)* | *(1.3)* | *(0.5)* | *(2.8)* |
| CCR | 2.81 | 0.28 | 1.04 | 0.49 | 2.44 | 0.28 | 1.89 | 0.34 |
| | *(1.2)* | *(3.7)* | *(0.1)* | *(3.3)* | *(0.7)* | *(3.0)* | *(1.2)* | *(5.4)* |
| STUR | 0.52 | 0.67 | 0.93 | 0.53 | 1.35 | 0.35 | 0.82 | 0.57 |
| | *(1.8)* | *(6.8)* | *(0.2)* | *(2.8)* | *(0.8)* | *(2.6)* | *(0.7)* | *(5.2)* |
| MUR | 2.12 | 0.32 | 1.32 | 0.41 | 2.16 | 0.32 | 1.73 | 0.35 |
| | *(1.2)* | *(3.7)* | *(0.6)* | *(3.5)* | *(0.7)* | *(3.2)* | *(1.4)* | *(5.8)* |
| UIR | 0.84 | 0.60 | 0.64 | 0.83 | 0.95 | 0.53 | 0.75 | 0.68 |
| | *(0.4)* | *(2.1)* | *(1.2)* | *(2.9)* | *(0.1)* | *(2.0)* | *(1.1)* | *(3.4)* |
| UOR | 0.50 | 0.86 | 1.17 | 0.27 | 1.95 | 0.11 | 1.00 | 0.50 |
| | *(2.2)* | *(4.1)* | *(0.4)* | *(0.5)* | *(0.8)* | *(0.7)* | *(0.0)* | *(2.6)* |
| NER | 2.15 | 0.30 | 1.46 | 0.34 | 1.78 | 0.28 | 1.77 | 0.32 |
| | *(0.8)* | *(4.1)* | *(0.6)* | *(2.3)* | *(0.7)* | *(1.4)* | *(1.0)* | *(4.5)* |
| WNER | 2.30 | 0.30 | 1.43 | 0.28 | 2.11 | 0.20 | 1.85 | 0.29 |
| | *(0.9)* | *(4.4)* | *(0.6)* | *(1.6)* | *(0.8)* | *(1.3)* | *(1.2)* | *(4.4)* |
| LJOBS | 1.63 | 0.36 | 1.40 | 0.37 | 1.60 | 0.32 | 1.51 | 0.36 |
| | *(0.8)* | *(4.7)* | *(1.0)* | *(3.6)* | *(0.7)* | *(1.7)* | *(1.3)* | *(5.9)* |
| VU | 0.56 | 0.90 | 2.02 | 0.28 | 2.78 | 0.15 | 1.54 | 0.34 |
| | *(2.3)* | *(4.3)* | *(0.6)* | *(3.5)* | *(0.6)* | *(0.9)* | *(0.7)* | *(3.7)* |
| VIU | 0.58 | 0.85 | 1.42 | 0.40 | 1.69 | 0.29 | 1.13 | 0.46 |
| | *(2.0)* | *(3.8)* | *(0.4)* | *(2.8)* | *(0.9)* | *(1.9)* | *(0.3)* | *(3.5)* |
| VUI | 0.38 | 0.90 | 2.62 | 0.16 | 1.16 | 0.43 | 1.58 | 0.32 |
| | *(2.5)* | *(4.2)* | *(0.6)* | *(1.5)* | *(0.3)* | *(2.0)* | *(0.6)* | *(2.7)* |
| SKILL | 0.90 | 0.55 | 2.42 | 0.09 | 1.36 | 0.29 | 1.70 | 0.23 |
| | *(0.2)* | *(2.2)* | *(0.5)* | *(0.4)* | *(0.8)* | *(1.3)* | *(0.6)* | *(1.3)* |
| LSXPUB | 1.51 | 0.22 | 1.11 | 0.38 | 1.91 | -0.19 | 1.36 | 0.23 |
| | *(0.5)* | *(0.7)* | *(0.3)* | *(0.9)* | *(1.3)* | *(1.4)* | *(0.8)* | *(1.0)* |
| LS | 1.31 | 0.29 | 1.29 | 0.24 | 3.19 | -0.19 | 1.52 | 0.15 |
| | *(0.4)* | *(0.8)* | *(0.5)* | *(0.6)* | *(0.9)* | *(1.8)* | *(1.0)* | *(0.8)* |

**Table C.2.4 (cont.)**

| Variable | 1985:1-1989:1 Rel. MSE | λ | 1990:1-1994:4 Rel. MSE | λ | 1995:1-2000:2 Rel. MSE | λ | 1985:1-2000:2 Rel. MSE | λ |
|---|---|---|---|---|---|---|---|---|
| Difference models | | | | | | | | |
| UR | 1.31 | 0.37 | 0.34 | 1.10 | 2.08 | 0.19 | 0.92 | 0.54 |
| | *(0.6)* | *(2.0)* | *(2.0)* | *(7.8)* | *(1.2)* | *(1.8)* | *(0.3)* | *(3.7)* |
| LUR | 1.61 | 0.32 | 0.29 | 1.01 | 2.41 | 0.13 | 1.05 | 0.48 |
| | *(0.6)* | *(1.8)* | *(2.1)* | *(10.2)* | *(1.1)* | *(1.0)* | *(0.2)* | *(3.5)* |
| CCR | 1.60 | 0.30 | 0.57 | 0.71 | 2.07 | 0.22 | 1.15 | 0.44 |
| | *(0.7)* | *(2.2)* | *(1.4)* | *(5.3)* | *(1.1)* | *(1.4)* | *(0.4)* | *(3.7)* |
| STUR | 1.22 | 0.39 | 0.73 | 0.70 | 1.87 | 0.25 | 1.05 | 0.47 |
| | *(0.5)* | *(2.7)* | *(1.5)* | *(5.8)* | *(0.8)* | *(1.6)* | *(0.3)* | *(4.8)* |
| MUR | 1.34 | 0.35 | 0.49 | 0.66 | 3.35 | 0.11 | 1.15 | 0.45 |
| | *(0.6)* | *(2.1)* | *(1.5)* | *(6.9)* | *(0.5)* | *(0.5)* | *(0.4)* | *(3.7)* |
| UIR | 1.00 | 0.51 | 0.95 | 0.67 | 1.79 | 0.25 | 1.07 | 0.40 |
| | *(0.0)* | *(2.2)* | *(0.6)* | *(2.3)* | *(1.2)* | *(1.7)* | *(0.7)* | *(3.1)* |
| UOR | 1.03 | 0.45 | 0.76 | 1.41 | 5.19 | -0.06 | 1.38 | 0.20 |
| | *(0.1)* | *(1.1)* | *(1.8)* | *(3.3)* | *(0.3)* | *(1.3)* | *(0.7)* | *(1.1)* |
| NER | 1.10 | 0.46 | 0.82 | 0.64 | 1.50 | 0.11 | 1.01 | 0.50 |
| | *(0.3)* | *(3.2)* | *(0.9)* | *(3.7)* | *(1.3)* | *(0.4)* | *(0.0)* | *(4.5)* |
| WNER | 1.23 | 0.43 | 1.14 | 0.42 | 2.82 | 0.10 | 1.37 | 0.37 |
| | *(0.3)* | *(2.7)* | *(0.4)* | *(2.4)* | *(0.6)* | *(0.5)* | *(0.8)* | *(3.3)* |
| LJOBS | 1.13 | 0.45 | 0.65 | 0.64 | 1.75 | 0.09 | 0.96 | 0.51 |
| | *(0.3)* | *(2.4)* | *(1.2)* | *(6.1)* | *(1.0)* | *(0.7)* | *(0.1)* | *(4.5)* |
| VU | 0.91 | 0.68 | 0.65 | 1.05 | 8.15 | -0.08 | 1.62 | 0.18 |
| | *(0.9)* | *(2.7)* | *(1.4)* | *(6.4)* | *(0.2)* | *(0.8)* | *(0.6)* | *(0.9)* |
| VIU | 0.84 | 0.85 | 0.43 | 1.21 | 6.23 | -0.03 | 1.26 | 0.35 |
| | *(1.5)* | *(3.9)* | *(2.0)* | *(10.3)* | *(0.3)* | *(0.2)* | *(0.5)* | *(1.5)* |
| VUI | 0.74 | 1.24 | 1.32 | 0.12 | 2.56 | 0.13 | 1.24 | 0.27 |
| | *(2.5)* | *(4.7)* | *(0.8)* | *(0.4)* | *(0.7)* | *(0.7)* | *(0.9)* | *(1.5)* |
| SKILL | 1.14 | 0.29 | 1.37 | -0.59 | 2.52 | -0.49 | 1.42 | -0.17 |
| | *(0.5)* | *(0.9)* | *(0.7)* | *(1.0)* | *(0.5)* | *(9.5)* | *(1.0)* | *(0.7)* |
| Combined forecasts | | | | | | | | |
| MEAN | 0.71 | 0.68 | 0.66 | 0.77 | 1.32 | 0.31 | 0.76 | 0.67 |
| | *(1.2)* | *(4.6)* | *(1.5)* | *(3.8)* | *(0.6)* | *(1.1)* | *(1.4)* | *(6.1)* |
| TRIM MEAN | 0.71 | 0.68 | 0.65 | 0.79 | 1.24 | 0.36 | 0.74 | 0.68 |
| | *(1.2)* | *(4.6)* | *(1.6)* | *(3.9)* | *(0.5)* | *(1.3)* | *(1.6)* | *(6.3)* |
| MEDIAN | 0.70 | 0.72 | 0.57 | 0.99 | 1.15 | 0.41 | 0.69 | 0.77 |
| | *(1.4)* | *(4.3)* | *(1.9)* | *(5.0)* | *(0.4)* | *(2.0)* | *(1.9)* | *(6.6)* |

Notes:
RMSE denotes the root mean squared error statistic.
Rel. MSE shows the mean squared error from each indicator relative to the MSE from the benchmark AR model
λ statistic is described in the text.
The numbers in parentheses are the associated t-ratios corrected for heteroscedasticity and autocorrelation, see Stock and Watson (1999). Note that in the case of Rel. MSE the null hypothesis is that this ratio equals one.
For variable definitions, see Table 3.1 or Annex A.

**Table C.2.5 – Forecasting performance of ten-year rolling-window models of RPIX inflation relative to AR benchmark**

| | 1985:1-1989:4 | | 1990:1-1994:4 | | 1995:1-2000:2 | | 1985:1-2000:2 | |
|---|---|---|---|---|---|---|---|---|
| Variable | Rel. MSE | λ | Rel. MSE | λ | Rel. MSE | λ | Rel. MSE | λ |
| AR baseline (% RMSE) | 1.55 | | 1.71 | | 0.65 | | 1.37 | |
| No change | 3.72 | 0.16 | 5.32 | -0.06 | 10.88 | 0.12 | 5.11 | 0.06 |
| | *(0.6)* | *(1.4)* | *(0.5)* | *(0.6)* | *(0.5)* | *(2.3)* | *(0.7)* | *(0.9)* |
| Import price Augmented | 1.84 | 0.22 | 1.06 | 0.21 | 1.09 | 0.42 | 1.39 | 0.23 |
| | *(1.2)* | *(2.4)* | *(0.7)* | *(0.8)* | *(0.4)* | *(2.7)* | *(1.22)* | *(2.7)* |
| Gap models | | | | | | | | |
| UR | 7.15 | 0.18 | 3.01 | 0.22 | 2.92 | 0.26 | 4.71 | 0.20 |
| | *(0.2)* | *(2.6)* | *(0.7)* | *(5.4)* | *(0.6)* | *(2.5)* | *(0.4)* | *(3.9)* |
| LUR | 6.46 | 0.18 | 1.59 | 0.35 | 4.89 | 0.11 | 3.87 | 0.21 |
| | *(0.3)* | *(2.8)* | *(0.8)* | *(3.2)* | *(0.5)* | *(1.1)* | *(0.5)* | *(3.6)* |
| CCR | 4.28 | 0.28 | 3.18 | 0.21 | 6.77 | 0.19 | 3.93 | 0.24 |
| | *(0.8)* | *(5.0)* | *(0.8)* | *(4.0)* | *(0.4)* | *(3.6)* | *(1.0)* | *(6.5)* |
| STUR | 1.19 | 0.46 | 1.24 | 0.38 | 2.32 | 0.31 | 1.31 | 0.41 |
| | *(0.2)* | *(3.1)* | *(0.9)* | *(3.2)* | *(1.0)* | *(4.7)* | *(0.7)* | *(5.3)* |
| MUR | 3.05 | 0.32 | 2.32 | 0.21 | 6.79 | 0.18 | 2.98 | 0.27 |
| | *(0.9)* | *(6.0)* | *(1.2)* | *(3.8)* | *(0.4)* | *(4.3)* | *(1.4)* | *(7.0)* |
| UIR | 1.37 | 0.41 | 1.06 | 0.43 | 2.29 | 0.29 | 1.29 | 0.39 |
| | *(0.5)* | *(3.3)* | *(0.4)* | *(2.0)* | *(1.0)* | *(5.1)* | *(0.8)* | *(4.5)* |
| UOR | 0.81 | 0.57 | 1.80 | 0.07 | 13.42 | 0.08 | 2.33 | 0.20 |
| | *(0.8)* | *(5.9)* | *(0.9)* | *(0.3)* | *(0.1)* | *(1.5)* | *(0.8)* | *(2.0)* |
| NER | 7.26 | 0.19 | 6.26 | 0.02 | 4.48 | 0.23 | 6.53 | 0.13 |
| | *(0.2)* | *(3.4)* | *(0.3)* | *(0.6)* | *(0.6)* | *(4.5)* | *(0.3)* | *(2.1)* |
| WNER | 8.84 | 0.13 | 3.19 | -0.06 | 4.47 | 0.24 | 5.63 | 0.11 |
| | *(0.2)* | *(3.4)* | *(0.7)* | *(0.4)* | *(0.6)* | *(6.9)* | *(0.4)* | *(2.5)* |
| LJOBS | 5.45 | 0.24 | 7.80 | -0.04 | 1.97 | 0.36 | 6.35 | 0.12 |
| | *(0.3)* | *(3.2)* | *(0.3)* | *(0.6)* | *(1.4)* | *(9.2)* | *(0.4)* | *(2.0)* |
| VU | 0.94 | 0.53 | 2.88 | 0.23 | 12.14 | 0.12 | 2.83 | 0.23 |
| | *(0.4)* | *(7.0)* | *(0.8)* | *(2.8)* | *(0.2)* | *(2.3)* | *(1.0)* | *(4.0)* |
| VIU | 0.99 | 0.51 | 1.52 | 0.36 | 7.99 | 0.16 | 1.82 | 0.31 |
| | *(0.0)* | *(2.9)* | *(0.9)* | *(3.8)* | *(0.4)* | *(2.9)* | *(1.4)* | *(4.4)* |
| VUI | 1.39 | 0.39 | 5.04 | 0.12 | 6.05 | 0.18 | 3.61 | 0.18 |
| | *(0.8)* | *(3.8)* | *(0.4)* | *(1.0)* | *(0.5)* | *(3.0)* | *(0.6)* | *(2.2)* |
| SKILL | 5.94 | -0.01 | 3.34 | 0.14 | 2.41 | 0.28 | 4.34 | 0.07 |
| | *(0.4)* | *(0.1)* | *(0.4)* | *(0.8)* | *(0.5)* | *(2.6)* | *(0.5)* | *(0.7)* |
| LSXPUB | 8.65 | 0.16 | 1.92 | 0.17 | 4.45 | -0.03 | 4.91 | 0.15 |
| | *(0.3)* | *(5.1)* | *(1.1)* | *(1.2)* | *(0.3)* | *(0.2)* | *(0.5)* | *(4.5)* |
| LS | 5.42 | 0.21 | 2.77 | 0.06 | 6.10 | -0.00 | 4.13 | 0.15 |
| | *(0.4)* | *(4.1)* | *(0.8)* | *(0.3)* | *(0.7)* | *(0.0)* | *(0.7)* | *(3.0)* |

**Table C.2.5 (cont.)**

| | 1985:1-1989:1 | | 1990:1-1994:4 | | 1995:1-2000:2 | | 1985:1-2000:2 | |
|---|---|---|---|---|---|---|---|---|
| Variable | Rel. MSE | λ | Rel. MSE | λ | Rel. MSE | λ | Rel. MSE | λ |
| Difference models | | | | | | | | |
| UR | 1.94 | 0.36 | 0.49 | 1.34 | 1.71 | 0.35 | 1.19 | 0.45 |
| | *(0.9)* | *(5.1)* | *(1.7)* | *(4.0)* | *(0.6)* | *(3.0)* | *(0.5)* | *(5.4)* |
| LUR | 7.56 | 0.19 | 1.13 | 0.46 | 3.84 | 0.18 | 4.01 | 0.23 |
| | *(0.3)* | *(3.5)* | *(0.2)* | *(3.6)* | *(0.4)* | *(1.9)* | *(0.5)* | *(3.9)* |
| CCR | 1.47 | 0.41 | 1.38 | 0.44 | 5.64 | 0.18 | 1.76 | 0.38 |
| | *(0.6)* | *(4.4)* | *(0.8)* | *(7.8)* | *(0.4)* | *(2.8)* | *(1.2)* | *(7.3)* |
| STUR | 2.18 | 0.27 | 0.93 | 0.56 | 3.72 | 0.21 | 1.67 | 0.30 |
| | *(0.7)* | *(5.8)* | *(0.3)* | *(2.7)* | *(0.4)* | *(1.8)* | *(1.1)* | *(5.0)* |
| MUR | 1.39 | 0.42 | 1.23 | 0.45 | 5.38 | 0.18 | 1.63 | 0.38 |
| | *(0.6)* | *(4.2)* | *(0.4)* | *(4.0)* | *(0.4)* | *(2.6)* | *(1.1)* | *(5.5)* |
| UIR | 1.78 | 0.25 | 0.87 | 0.60 | 5.27 | 0.18 | 1.60 | 0.30 |
| | *(1.1)* | *(2.7)* | *(0.5)* | *(3.1)* | *(0.3)* | *(2.6)* | *(1.3)* | *(3.7)* |
| UOR | 1.13 | 0.45 | 0.95 | 0.54 | 14.91 | 0.03 | 2.15 | 0.23 |
| | *(0.2)* | *(2.6)* | *(0.2)* | *(2.4)* | *(0.1)* | *(0.6)* | *(0.7)* | *(2.0)* |
| NER | 1.05 | 0.49 | 0.74 | 0.64 | 0.82 | 0.58 | 0.87 | 0.54 |
| | *(0.1)* | *(5.1)* | *(0.8)* | *(3.6)* | *(0.8)* | *(4.7)* | *(0.5)* | *(6.5)* |
| WNER | 1.68 | 0.39 | 2.73 | 0.26 | 5.57 | 0.15 | 2.53 | 0.29 |
| | *(0.7)* | *(4.4)* | *(0.5)* | *(2.5)* | *(0.4)* | *(2.0)* | *(0.7)* | *(4.1)* |
| LJOBS | 2.07 | 0.36 | 5.06 | 0.15 | 1.32 | 0.39 | 3.52 | 0.23 |
| | *(0.9)* | *(5.6)* | *(0.4)* | *(1.7)* | *(0.9)* | *(3.9)* | *(0.5)* | *(2.9)* |
| VU | 2.65 | 0.25 | 0.90 | 0.54 | 11.40 | 0.05 | 2.47 | 0.26 |
| | *(0.4)* | *(1.9)* | *(0.3)* | *(4.8)* | *(0.2)* | *(1.1)* | *(0.8)* | *(3.0)* |
| VIU | 2.58 | 0.30 | 0.58 | 0.84 | 19.11 | 0.07 | 2.90 | 0.24 |
| | *(0.8)* | *(3.9)* | *(1.4)* | *(5.0)* | *(0.1)* | *(1.6)* | *(0.7)* | *(3.2)* |
| VUI | 3.85 | 0.21 | 2.48 | 0.25 | 5.50 | 0.06 | 3.29 | 0.21 |
| | *(0.7)* | *(4.1)* | *(1.0)* | *(2.9)* | *(0.6)* | *(0.8)* | *(1.1)* | *(4.3)* |
| SKILL | 2.03 | 0.33 | 1.50 | 0.11 | 4.51 | 0.02 | 1.96 | 0.24 |
| | *(1.3)* | *(5.3)* | *(0.6)* | *(0.3)* | *(0.5)* | *(0.3)* | *(1.2)* | *(2.7)* |
| Combined forecasts | | | | | | | | |
| MEAN | 1.48 | 0.41 | 0.83 | 0.60 | 1.83 | 0.35 | 1.18 | 0.45 |
| | *(0.5)* | *(3.7)* | *(0.7)* | *(4.6)* | *(0.7)* | *(4.3)* | *(0.5)* | *(5.2)* |
| TRIM MEAN | 1.44 | 0.42 | 0.82 | 0.61 | 1.72 | 0.37 | 1.15 | 0.46 |
| | *(0.4)* | *(3.7)* | *(0.8)* | *(4.7)* | *(0.7)* | *(4.5)* | *(0.4)* | *(5.1)* |
| MEDIAN | 0.99 | 0.50 | 0.76 | 0.70 | 1.23 | 0.45 | 0.90 | 0.54 |
| | *(0.0)* | *(3.5)* | *(1.1)* | *(4.0)* | *(0.6)* | *(7.9)* | *(0.4)* | *(5.1)* |

Notes:
RMSE denotes the root mean squared error statistic.
Rel. MSE shows the mean squared error from each indicator relative to the MSE from the benchmark AR model
λ statistic is described in the text.
The numbers in parentheses are the associated t-ratios corrected for heteroscedasticity and autocorrelation, see Stock and Watson (1999). Note that in the case of Rel. MSE the null hypothesis is that this ratio equals one.
For variable definitions, see Table 3.1 or Annex A.

**Table C.2.6 – Forecasting performance of ten-year rolling-window models of AEI inflation relative to AR benchmark**

| | 1985:1-1989:4 | | 1990:1-1994:4 | | 1995:1-2000:2 | | 1985:1-2000:2 | |
|---|---|---|---|---|---|---|---|---|
| Variable | Rel. MSE | λ | Rel. MSE | λ | Rel. MSE | λ | Rel. MSE | λ |
| AR baseline (% RMSE) | 1.80 | | 1.75 | | 1.03 | | 1.55 | |
| No change | 1.51 | -0.0 | 1.90 | -0.12 | 1.25 | 0.30 | 1.63 | -0.01 |
| | *(2.1)* | *(0.0)* | *(1.2)* | *(0.5)* | *(0.8)* | *(1.4)* | *(1.6)* | *(0.1)* |
| Import price Augmented | 0.81 | 0.99 | 1.08 | -0.30 | 1.55 | -0.81 | 1.04 | 0.36 |
| | *(1.0)* | *(2.4)* | *(0.9)* | *(0.9)* | *(0.7)* | *(1.3)* | *(0.3)* | *(0.8)* |
| Gap models | | | | | | | | |
| UR | 3.03 | 0.32 | 2.14 | 0.30 | 2.04 | 0.03 | 2.51 | 0.30 |
| | *(0.6)* | *(7.6)* | *(0.5)* | *(2.4)* | *(0.9)* | *(0.2)* | *(0.8)* | *(6.0)* |
| LUR | 1.98 | 0.38 | 2.53 | 0.27 | 1.96 | 0.00 | 2.20 | 0.32 |
| | *(0.6)* | *(9.1)* | *(0.4)* | *(2.0)* | *(1.0)* | *(0.0)* | *(0.7)* | *(4.5)* |
| CCR | 2.36 | 0.36 | 2.06 | 0.32 | 3.29 | -0.07 | 2.38 | 0.31 |
| | *(0.9)* | *(5.3)* | *(0.6)* | *(3.4)* | *(0.6)* | *(0.3)* | *(1.2)* | *(5.4)* |
| STUR | 1.34 | 0.44 | 1.39 | 0.38 | 1.72 | -0.20 | 1.42 | 0.40 |
| | *(0.8)* | *(10.1)* | *(0.5)* | *(2.7)* | *(1.1)* | *(0.7)* | *(1.0)* | *(6.1)* |
| MUR | 2.08 | 0.37 | 2.34 | 0.30 | 2.25 | 0.12 | 2.21 | 0.32 |
| | *(0.8)* | *(4.5)* | *(0.6)* | *(3.4)* | *(0.8)* | *(0.8)* | *(1.0)* | *(5.3)* |
| UIR | 1.38 | 0.42 | 1.28 | 0.38 | 1.68 | -0.00 | 1.39 | 0.38 |
| | *(0.4)* | *(2.9)* | *(0.6)* | *(2.9)* | *(0.9)* | *(0.0)* | *(0.8)* | *(3.6)* |
| UOR | 0.62 | 0.81 | 0.70 | 0.66 | 1.44 | 0.19 | 0.78 | 0.64 |
| | *(1.2)* | *(3.3)* | *(1.4)* | *(5.2)* | *(1.1)* | *(0.8)* | *(1.2)* | *(5.6)* |
| NER | 2.39 | 0.35 | 1.16 | 0.45 | 1.42 | 0.35 | 1.74 | 0.37 |
| | *(0.5)* | *(7.1)* | *(0.3)* | *(3.0)* | *(0.4)* | *(1.5)* | *(0.8)* | *(6.9)* |
| WNER | 2.81 | 0.32 | 2.24 | 0.27 | 1.66 | 0.04 | 2.39 | 0.30 |
| | *(0.6)* | *(5.9)* | *(0.7)* | *(3.8)* | *(1.1)* | *(0.2)* | *(0.9)* | *(6.5)* |
| LJOBS | 2.37 | 0.34 | 1.51 | 0.35 | 1.66 | 0.17 | 1.91 | 0.33 |
| | *(0.9)* | *(6.2)* | *(0.9)* | *(2.8)* | *(0.9)* | *(1.1)* | *(1.3)* | *(6.4)* |
| VU | 1.32 | 0.39 | 2.12 | 0.30 | 1.70 | 0.31 | 1.70 | 0.33 |
| | *(0.5)* | *(2.6)* | *(0.5)* | *(3.9)* | *(0.6)* | *(1.8)* | *(0.8)* | *(4.8)* |
| VIU | 0.58 | 0.79 | 1.54 | 0.38 | 1.81 | 0.10 | 1.16 | 0.44 |
| | *(1.1)* | *(2.9)* | *(0.5)* | *(3.4)* | *(1.0)* | *(0.6)* | *(0.4)* | *(3.6)* |
| VUI | 0.71 | 0.61 | 3.14 | 0.20 | 1.65 | 0.17 | 1.85 | 0.30 |
| | *(0.7)* | *(3.7)* | *(0.6)* | *(3.0)* | *(0.9)* | *(0.7)* | *(0.8)* | *(3.3)* |
| SKILL | 1.28 | 0.44 | 2.02 | 0.24 | 1.73 | -0.19 | 1.65 | 0.32 |
| | *(0.5)* | *(3.8)* | *(0.6)* | *(1.6)* | *(1.2)* | *(0.6)* | *(1.0)* | *(3.0)* |
| LSXPUB | 4.31 | 0.27 | 2.30 | 0.27 | 2.07 | 0.07 | 3.14 | 0.26 |
| | *(0.3)* | *(7.5)* | *(0.8)* | *(2.1)* | *(0.8)* | *(0.5)* | *(0.6)* | *(6.0)* |
| LS | 3.25 | 0.30 | 3.17 | 0.18 | 0.97 | 0.51 | 2.86 | 0.27 |
| | *(0.4)* | *(6.4)* | *(0.9)* | *(1.6)* | *(0.1)* | *(3.0)* | *(0.8)* | *(5.4)* |

**Table C.2.6 (cont.)**

| | 1985:1-1989:1 | | 1990:1-1994:4 | | 1995:1-2000:2 | | 1985:1-2000:2 | |
|---|---|---|---|---|---|---|---|---|
| Variable | Rel. MSE | λ | Rel. MSE | λ | Rel. MSE | λ | Rel. MSE | λ |
| Difference models | | | | | | | | |
| UR | 1.99 | 0.37 | 0.70 | 0.62 | 1.26 | 0.27 | 1.35 | 0.42 |
| | *(0.9)* | *(4.1)* | *(1.1)* | *(5.0)* | *(0.6)* | *(0.9)* | *(0.8)* | *(5.6)* |
| LUR | 2.09 | 0.36 | 0.97 | 0.51 | 1.12 | 0.41 | 1.48 | 0.40 |
| | *(0.8)* | *(4.1)* | *(0.1)* | *(4.5)* | *(0.3)* | *(1.5)* | *(0.8)* | *(5.4)* |
| CCR | 2.51 | 0.30 | 1.18 | 0.45 | 1.42 | 0.25 | 1.80 | 0.34 |
| | *(0.5)* | *(3.0)* | *(0.3)* | *(3.5)* | *(0.5)* | *(0.8)* | *(0.7)* | *(3.9)* |
| STUR | 0.66 | 0.60 | 1.09 | 0.47 | 1.13 | 0.32 | 0.91 | 0.53 |
| | *(1.0)* | *(9.7)* | *(0.2)* | *(3.1)* | *(0.5)* | *(0.9)* | *(0.4)* | *(5.9)* |
| MUR | 2.35 | 0.29 | 1.25 | 0.44 | 1.04 | 0.48 | 1.69 | 0.35 |
| | *(0.5)* | *(2.7)* | *(0.4)* | *(3.4)* | *(0.1)* | *(1.6)* | *(0.7)* | *(3.9)* |
| UIR | 5.10 | 0.12 | 1.77 | 0.31 | 1.15 | 0.13 | 3.12 | 0.17 |
| | *(0.3)* | *(1.9)* | *(0.5)* | *(2.2)* | *(1.0)* | *(0.4)* | *(0.5)* | *(2.5)* |
| UOR | 0.80 | 0.57 | 1.23 | 0.40 | 1.30 | 0.38 | 1.05 | 0.48 |
| | *(0.5)* | *(3.8)* | *(0.6)* | *(3.4)* | *(0.9)* | *(2.6)* | *(0.2)* | *(5.3)* |
| NER | 1.43 | 0.43 | 0.61 | 0.72 | 0.85 | 0.62 | 1.01 | 0.50 |
| | *(0.8)* | *(5.3)* | *(1.4)* | *(3.7)* | *(0.6)* | *(3.0)* | *(0.0)* | *(6.7)* |
| WNER | 2.04 | 0.36 | 1.98 | 0.27 | 1.28 | 0.22 | 1.90 | 0.32 |
| | *(0.8)* | *(3.9)* | *(0.6)* | *(2.6)* | *(0.8)* | *(0.9)* | *(1.0)* | *(4.3)* |
| LJOBS | 1.55 | 0.40 | 0.97 | 0.51 | 0.97 | 0.53 | 1.22 | 0.44 |
| | *(0.7)* | *(3.8)* | *(0.1)* | *(3.8)* | *(0.1)* | *(1.5)* | *(0.6)* | *(5.4)* |
| VU | 2.89 | 0.26 | 0.70 | 0.75 | 4.49 | 0.20 | 2.25 | 0.28 |
| | *(0.5)* | *(3.0)* | *(1.7)* | *(4.7)* | *(0.4)* | *(1.8)* | *(0.7)* | *(3.8)* |
| VIU | 1.14 | 0.47 | 1.03 | 0.49 | 1.56 | 0.33 | 1.16 | 0.45 |
| | *(0.4)* | *(6.5)* | *(0.1)* | *(4.8)* | *(0.8)* | *(2.0)* | *(0.8)* | *(7.8)* |
| VUI | 0.52 | 0.65 | 1.07 | 0.47 | 1.85 | 0.32 | 0.95 | 0.52 |
| | *(1.3)* | *(5.7)* | *(0.2)* | *(3.0)* | *(0.5)* | *(1.9)* | *(0.2)* | *(5.4)* |
| SKILL | 6.59 | 0.21 | 1.55 | 0.35 | 2.02 | -0.65 | 3.81 | 0.22 |
| | *(0.3)* | *(3.1)* | *(1.4)* | *(6.2)* | *(1.5)* | *(2.5)* | *(0.5)* | *(3.7)* |
| Combined forecasts | | | | | | | | |
| MEAN | 0.80 | 0.54 | 0.92 | 0.53 | 0.98 | 0.52 | 0.88 | 0.54 |
| | *(0.6)* | *(7.9)* | *(0.2)* | *(3.3)* | *(0.1)* | *(1.2)* | *(0.6)* | *(7.4)* |
| TRIM MEAN | 0.76 | 0.55 | 0.91 | 0.54 | 1.00 | 0.50 | 0.86 | 0.55 |
| | *(0.7)* | *(8.0)* | *(0.3)* | *(3.3)* | *(0.0)* | *(1.2)* | *(0.7)* | *(7.4)* |
| MEDIAN | 0.71 | 0.58 | 0.89 | 0.55 | 1.10 | 0.38 | 0.84 | 0.56 |
| | *(0.8)* | *(7.3)* | *(0.3)* | *(3.2)* | *(0.3)* | *(1.0)* | *(0.7)* | *(6.9)* |

Notes:
RMSE denotes the root mean squared error statistic.
Rel. MSE shows the mean squared error from each indicator relative to the MSE from the benchmark AR model
λ statistic is described in the text.
The numbers in parentheses are the associated t-ratios corrected for heteroscedasticity and autocorrelation, see Stock and Watson (1999). Note that in the case of Rel. MSE the null hypothesis is that this ratio equals one.
For variable definitions, see Table 3.1 or Annex A.

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