NEW METHODS FORECASTING INFLATION AND ITS SUB-COMPONENTS: APPLICATION TO THE USA

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"New methods for forecasting inflation and its sub-components: application to the USA."

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August, 2008

Abstract:
Forecasts are presented for the 12-month ahead US rate of inflation measured by the chain weighted personal consumer expenditure deflator, \( PC \), and its three main components: non-durable goods, durable goods and services. Monthly models are estimated for 1974 to 1999, and pseudo out-of-sample forecasting performance is examined for 2000-2007. Alternative forecasting approaches for a number of different information sets are compared with benchmark univariate autoregressive models. In general, substantial out-performance is demonstrated for the aggregate and components models relative to benchmark models. The combination of equilibrium correction terms, which bring gradual adjustment of relative prices into the inflation process, and non-linearities, to proxy state dependence in the inflation process, is shown to contribute importantly to this out-performance. There is also evidence that forecast pooling or averaging improves forecast performance. The indirect forecasts constructed by weighting the three component forecasts are compared with the direct forecasts from the aggregate \( PC \). In most cases, the indirect method outperforms the direct method. A key innovation is to compare standard AR or VAR methods of using an information criterion to select the lag length, with a parameterization in which longer lags appear in parsimonious forms. Another is to compare general unrestricted models with corresponding parsimonious models selected by Autometrics, Doornik (2008).

JEL codes: E31, E37.

Key words: inflation forecasting, US inflation, inflation components.

* The authors acknowledge funding support from the Economic and Social Research Council, U.K. (grant RES-000-22-2066). Comments from John V. Duca of the Dallas Federal Reserve are gratefully acknowledged but errors are the authors’ sole responsibility.
1. Introduction

Stabilising inflation is one objective of monetary policy in the USA, while a large subset of OECD and a few emerging market countries now target inflation as a primary objective of policy. Since monetary policy is based on the likely path of inflation, it is important that the central bank has a reliable forecasting framework. In recent years, new emphasis has been given to predicting inflationary trends. Semi-annual short-term inflation forecasts are published by the Federal Reserve (for the core personal consumption expenditure deflator); and quarterly short-term forecasts of inflation are published by the Bank of England, with, since 1999, an annual evaluation of its forecasting record. Forecasts of macroeconomic aggregates, including inflation, are also made by the private sector, governmental and international institutions. Such forecasts can influence inflationary expectations that serve as a nominal anchor in wage and other contracts such as housing, rents and interest rates.

Forecasters employ a range of different approaches to forecast inflation. Most inflation models tend to forecast the overall price index, e.g. the consumer price index (CPI) or the deflator of personal consumer expenditure (PCE) which we denote by $PC$. A less formal approach examines trends in different sub-components of the price index, such as price indices for food, fuel, durable goods, financial and other services, housing and others. These trends are then projected ahead, often using fairly crude methods, both within central banks and by private sector analysts. A more formal disaggregated approach has been explored for the USA, but only with differenced models, i.e. for inflation rates rather than price levels. Recently there has been renewed interest, mainly by central banks, in whether there is a potential improvement in forecast accuracy from forecasting the sub-component indices of the CPI and aggregating these forecasts, as against forecasting the aggregate itself.

In practice, disaggregating the price index into its sub-components can increase information in the forecasting process. Hypotheses about sectoral transmission of policy and shocks are often more specific than hypotheses about overall transmission. For example, prices in the service sector are likely to be less affected by the exchange rate than are prices for internationally traded consumer durables. The econometric specifications can be allowed to vary across disaggregated components, and dynamic properties of individual components may be better captured than standardising the dynamic response across sectors in an aggregate model. Modelling the individual components makes sense as different information sets apply to different sectors. The
importance of technological innovation, taxation and the extent of competition may vary across components.

A graphic illustration is given by the diverging paths in USA goods and services prices sub-totals, highlighted by Peach et al. (2004). In relative price terms, illustrated in Figure 1, the overall PCE deflator, PC, has risen relative to durable goods almost monotonically for four decades, while the opposite is true relative to services since 1980. The general index relative to the index for non-durables is much more erratic, showing the stronger influence of food and energy prices on prices of non-durable goods. The chain weighted overall price index is effectively defined by linking together the monthly log changes of the components weighted by their respective shares in total expenditure. These shares are illustrated in Figure 2: the share of services has increased from around 44 percent in 1970 to around 60 percent in 2007, while the share of non-durable goods has declined from 42 percent to 29 percent over the same period. The share of durables goods has hovered in the 11 to 14 percent range, but subject to a little drift towards the lower end of this range.

Theory suggests that aggregating sub-component forecasts is superior to directly forecasting the aggregate if the data generating process is known.\(^1\) When aggregating these sub-component forecasts, the forecast errors of the components may in part cancel out, further improving the accuracy of the aggregate forecast constructed in this way (Clements and Hendry, 2002). This is not necessarily the case, however, as exogenous shocks might drive the forecast errors of some disaggregate variables in the same direction - as Hubrich (2005) appears to find for Euro Area inflation from oil and unprocessed food price shocks. In practice, models for the disaggregated variables may not be correctly specified (see Grunfeld & Griliches, 1960, Zellner and Tobias, 2000). Predictive improvements can also be off-set by model selection uncertainty, estimation uncertainty, changing collinearity, structural breaks over the forecast horizon and measurement errors (see Hendry and Hubrich, 2006). Further, a well specified model in-sample does not necessarily imply higher forecast accuracy.

We review below the relatively sparse formal econometric models in the literature aggregating CPI component forecasts to help forecast the overall price index. The majority of studies apply to

the Euro area, and two to the USA – none for the UK or other countries. These studies almost all focus on differential inflation rates, omitting long-run relationships and the key role of relative prices. Many determinants of inflation are excluded in simple Vector Autoregressive (VAR) models that are constrained by degrees of freedom problems. Regime changes, such as the possible effect on inflation of increased openness to trade, are never treated.

The focus on differential inflation rates is common to most models of aggregate inflation too, where the New Keynesian Phillips curve currently tends to dominate. In its pure form, this expresses current inflation in terms of expected inflation with a coefficient close to one, and in terms of the output gap. The hybrid form adds lagged inflation with the sum of expected and lagged inflation close to 1, the “accelerationist” restriction. Stock and Watson’s influential 2003 paper is in the accelerationist form. Generalisations of the New Keynesian model, see Angeloni et al (2006) for a summary, use the deviation of the mark-up of prices on costs from the steady state value (often proxied by the wage share of national income or the ratio of the unit labour cost to the output price index). This does, however, bring in one important relative price.

Our paper is concerned with the economic drivers of the aggregate and the individual components of the 12-month-ahead chained consumer expenditure deflator (PC) in the US. We prefer the PCE deflator to the CPI since the latter underwent a major shift in methodology in 1983, when the treatment of homeowners’ costs shifted from a mortgage cost basis to an imputed rent basis. Furthermore, changes in the treatment of quality change are likely to have made the CPI less consistent over time. Durable goods, non-durable goods and services have very different inflation histories. Figure 3 shows the log levels of the PC and sub-indices, Figure 4 shows the monthly log changes and Figure 5 the annual log differences. Durables goods have experienced negative inflation for the last decade, while non-durable goods only occasionally experience price falls over a 12-month period. Prices of services have not fallen in any 12-month period in the last four decades. If different factors drive inflation in the three main components of total expenditure, then weighting separate forecasts of the three inflation rates might produce better forecasts of the overall inflation rate.

Aggregate PC inflation is forecast, both directly, and indirectly, via a weighted aggregation of the inflation forecasts of components. A comprehensive framework is developed to estimate component inflation models to check whether more accurate overall inflation forecasting is possible by aggregating such forecasts. We are careful to incorporate shocks to energy and other
commodities, which feed through into the PC price components via wholesale and import prices. Unusual or innovative features of our approach include the following. The h-step forecasting method (see Stock and Watson, 1999) is used, and we exploit long-run information in relative prices and trends in technology, trade openness and other indicators. Plausible restrictions are applied to overcome the ‘curse of dimensionality’ in order to select parsimonious models. The role of non-linearities is explored and the contribution of automatic model selection methods is examined.

Forecasting performance for both the aggregate and its sub-components is compared with benchmark models from the literature. Much evidence has accumulated, see for example, Stock and Watson (1999, 2003), that simple univariate autoregressive models are hard to beat in pseudo-out of sample forecasting evaluations. Our work throws light on the factors likely to improve forecasting performance. For example, does working with first differences of non-stationary data tend to improve performance, because of greater robustness to structural breaks, see Hendry and Clements (2003)? Or is it better to try to exploit possible cointegration properties of non-stationary data? Does model selection using Autometrics (Doornik, 2008) improve forecasting performance relative to naïve models?

We also explore whether other restrictions can improve forecasting performance. VARs aim to preserve generality by not imposing a priori structure on models, (Sims, 1980), but suffer from the ‘curse of dimensionality’ as increases in lag lengths or in the number of variables covered rapidly raise the number of parameters to be estimated. In practice, their gain in generality comes at the cost of restricting the number of variables and lag lengths that can be considered. One way of achieving a better trade-off between these objectives is to impose other restrictions. For example, for variables in differences in this paper we allow full generality at short lag lengths but restrict lags at 3 months or longer to appear as Δ3, as Δ6 if 6 months or longer and Δ12 if 12 months or longer. For variables in levels, we use 3-month or 12-month moving averages as alternatives to the monthly level. Formulating the ‘general unrestricted model’ (GUM) in this way has potential benefits in enabling longer lags to play a role and permitting smoother responses to shocks. When using automatic model selection methods, these formulations can result in the selection of more parsimonious models. We put these ideas to the test by asking whether such models have better forecasting performance than more standard models. We also impose some minimal sign restrictions on our models, for example, requiring equilibrium correction terms to
have signs consistent with such correction, and ensuring that output gaps or their proxies have a positive effect on future inflation.

These models potentially lend insight into underlying inflationary trends e.g. from the labour, import, energy and housing markets. They may stimulate research into the role of sectoral heterogeneity in inflation dynamics. One concerns the implications for monetary policy through different monetary transmission channels. Our models contain several direct and indirect channels for monetary policy transmission, e.g. through the output gap or unemployment rate, the exchange rate and domestic asset prices. The treatment of housing costs in the PC price index, for example, has important inflationary implications depending on the pass-through from house prices and interest rates into rents. Thus, policy-relevant topical economic questions can be addressed, though within the limitations of a reduced form forecasting framework. These include studying the implications for inflation of the decline in US house prices and of the unwinding of the commodity price rises of 2008.

A second question concerns the causes of the reduction since the early 1980s in inflation and in its volatility, an aspect of the ‘great moderation’ (Bernanke, 2004). Some have suggested that improved monetary policy from around 1980 is an important explanation. Others have emphasized the globalization of trade and finance, changes in technology, the decline of trade unions, and the rise of the “Asian tigers”. Yet others claim that the greater stability of the last two decades has been largely a matter of luck. Our modeling approach should throw some modest light on these hypotheses, although it is always difficult to identify unambiguously the role of trending variables. Some of these variables examined in our models are measures of openness, the share of Asian producers in global exports of manufactures and union density, illustrated in Figure 6.

A third question considers whether the speed of price adjustment has fallen with a lower inflation volatility environment. There is a large literature on inflation persistence and price stickiness, recently intensively studied at the micro as well as macro level by the Inflation Persistence Network set up by the ECB and main central banks from round the world, see Angeloni et al (2006), Altissimo et al (2005) and Alvarez et al (2005). One of the key issues concerns whether the probability of price changes is state dependent, as argued by Sheshinski and Weiss (1977), or whether the popular Calvo model, the work-horse of modern monetary economics, applies. Reis (2006) supports state dependence: in his sticky information model, producers will re-optimise
more frequently when cost changes are more volatile, suggesting a higher speed of adjustment in high inflation periods such as the 1970s. One plausible implication of these ideas is that there could be non-linearities in the inflation process so that high current or recent rates of inflation are associated with disproportionately higher future inflation. Our models explore this question by testing for such non-linearities.

2. Literature survey of disaggregated inflation forecasting studies

We present in Table 1 a chronological analytical summary of known disaggregation studies of inflation.

Most of the small number of empirical studies that address whether the accuracy of forecasts of aggregate inflation can be improved by disaggregation, focus on the Euro Area, using the Harmonised Index of Consumer Prices (HICP). The only other application of disaggregation is to the USA – none to the UK, other OECD countries or emerging market countries. Results from these studies provide mixed evidence about the relative benefit of employing the disaggregate approach. But this needs to be taken with the caveat that some use potentially mis-specified forecasting models (and in the Euro Area, over brief samples). Table 1 notes the near-universal omission of long-run equilibrium relationships and the exclusion of many theoretically-relevant determinants of inflation, including relative prices. The majority of studies estimate model only using differences in log prices. While differencing can help avoid the forecast failure from structural breaks, a common source of forecast failure (Hendry and Clements, 2003), the feedback relationships that help tie down sectoral price behaviour in the medium-run is missing. Research is needed on whether differencing really improves forecasting performance or whether longer-run information adds value.

One USA study finds for simple differenced ARIMA models that the improvement in the root mean squared error of one-year-ahead forecasts with the disaggregated approach is more than 20 percent (Espasa et al, 2002). Peach et al. (2004) explore the behaviour of the gap between USA goods and services price inflation and find it exhibits mean reversion in the long-run. They add the inflation gap to simple models for the change in inflation of goods and services prices. They use these models to forecast the disaggregated price inflation only, and find they compare well in forecastability with popular models. Hendry and Hubrich (2006) explore the different issue of
whether adding components, or subsets of components, to aggregate price forecasts, enhances those forecasts. They show theoretically that disaggregate information does help predictability, and improves forecasts of US inflation, in particular for a longer sample period from 1980 to 2004.

Turning to the Euro Area studies, Hubrich (2005) explores differing selection procedures, but in short samples, is confined to differenced VARs and univariate models. She finds the indirect method inferior to forecasting aggregate Euro Area year-on-year inflation directly for horizons of 12 months. In contrast, Hubrich finds that the indirect approach works better for ‘core’ inflation (HICPX), when excluding difficult-to-forecast components such as energy and unprocessed food prices. This suggests there are gains to be made by better forecasting of some sectoral prices. This exact conclusion was reached by Fritzer et al (2002), in a study on Austria, where better sectoral determinants proved helpful. He finds the disaggregated approach substantially improves forecasting accuracy for HICP using differenced ARIMA models; while in VAR models specified in levels (with a trend) the disaggregated approach is superior using 10 to 12 months ahead horizons. A later study by some of the same authors for Austria also favours the aggregation of sub-indices forecasts, though using differenced VARs (Moser et al, 2004). This study is notable for the large set of sector-specific variables it uses. The differenced VAR study by Benalal et al (2004), also using a fairly rich set of sectoral determinants, finds the direct approach provides clearly better results than the indirect approach for 12 and 18 steps ahead for the overall HICP, while for shorter horizons the results are mixed. Again, for HICPX, the indirect forecast outperforms the direct. A Dutch study (den Reijer and Vlaar, 2004) finds little difference for Euro Area HICP between direct and indirect methods, but employ rather spartan differenced VARs. Finally, Espasa and various co-authors in several papers on the Euro Area (see Table 1) try to incorporate long-run information, either by including cointegrating vectors of country HICPs in differenced VARs; or by combining forecasts from a quarterly cointegration model with more ambitious inflation determinants, and a purely price-based monthly forecasting model. In all of this last set of studies, there are improvements for the indirect approach, using disaggregated price information and modelling.

3. **Forecasting aggregate consumer price inflation**
In this section, we ignore information on the sub-components of PCE inflation and forecast PC directly using various information sets. The dependent variable is the h-step-ahead rate of aggregate inflation in single equation equilibrium correction models or simpler variants of these, where h is 12 months. Multi-step models for inflation forecasting have been popularised by Stock and Watson (1999, 2003). Methodologically, multi-step models can be regarded as single equation, reduced-forms of the related VAR system. Some research suggests that where VAR models suffer from specification errors such as omitted moving average error components or certain kinds of structural breaks, single-equation, multi-step models can sometimes provide more robust forecasts (Weiss, 1991; Clements and Hendry, 1996, 1998).

We contrast a wide range of information sets and check whether automatic model selection within each brings advantages. The simplest is a univariate autoregressive model for inflation rates. It is standard in the VAR and the multi-step forecasting literature based on VARs to use the Akaike or Schwarz information criterion (AIC or BIC) to choose the maximum lag length of the model and the same is done here. We contrast an unrestricted model with the more parsimonious lag structure discussed above. Let \( \Delta \log PC_t \) denote \( \log PC_t - \log PC_{t-j} \). Thus an AR(k+1) or VAR(k+1) includes \( \Delta \log PC_{t-i} \) for \( i=0, k \), where the forecast variable is for \( t+h \), with \( h > 0 \). Our preferred parsimonious longer lag (PLL) alternative includes \( \Delta \log PC_{t-3} \), \( \Delta \log PC_{t-6} \), and \( \Delta \log PC_{t-12} \). As noted above, this is a parsimonious way of allowing longer lags to enter, using 6 parameters to summarise 24 lags.

The forecasting performance from various extensions of the information set is reported in Table 3. The information set is extended by adding a time trend, changes in the unemployment rate, and trending variables such as union density. A further expansion of the information set is to add log changes in the producer price index, labour earnings, import prices, the real exchange rate and oil prices, and then equilibrium correction terms and non-linearities. In all, twelve information sets are considered, and the forecasting performance of three different methodologies are compared. The first uses a standard AR(k+1) or VAR(k+1) specification in changes of the key log price or cost, log real exchange rate, unemployment rate variables, where the maximum lag length k is chosen using BIC. The second uses our parsimonious longer lag (PLL) structure, and the third applies automatic model selection to the latter. The models are now discussed in further detail.

3.1 The specific modelling framework
To be specific, the single-equation reduced form VAR(k) version of the equation which does not impose the $\Delta_3$, $\Delta_6$ and $\Delta_{12}$ restrictions and includes ECM terms is as follows:

$$
\Delta_h \log PC_{t+h} = \alpha + \eta (\log PPI_t - \log PC_t) + \sum_{j=0}^{k} \eta_j \Delta \log PPI_{t-j} \\
+ \theta (\log ULC_t - \log PC_t) + \sum_{j=0}^{k} \theta_j \Delta \log EARN_{t-j} \\
+ \lambda (\log PIMP_t - \log PC_t) + \sum_{j=0}^{k} \lambda_j \Delta \log PIMP_{t-j} \\
+ \varphi (\log OTHERP_t - \log PC_t) + \sum_{j=0}^{k} \varphi_j \Delta \log OTHERP_{t-j} \\
+ \sum_{i=1}^{n} \beta_i X_{t,i} + \sum_{i=1}^{n} \sum_{j=0}^{k} \beta_{i,j} \Delta X_{t,i,j} \\
+ \sum_{j=0}^{k} \omega_j \Delta \log PC_{t-j} + \text{trends}_t + \epsilon_t
$$

For $h=12$, $PC_{t+12}$ is the 12-month ahead value of the price index. $PPI$ is a producer price index, $ULC$ is unit labour costs, $PIMP$ is an index of import prices (excluding petroleum products). $OTHERP$ includes other prices such as oil prices ($POIL$) and house prices ($HP$). Since unit labour costs are not available monthly, $ULC$ is the 3-month moving average of interpolated quarterly data, lagged 2 months given lags in availability of the quarterly data in real time. For the dynamics, changes in log $ULC$ are replaced by changes in log $EARN$, earnings per person hour in the private sector, which are monthly. The variables in X include the log real exchange rate ($REER$), the unemployment rate ($UNR$) or other measures of the output gap. The trends could include variables such as trade union density ($UNDENS$), trade openness, or the share of Asian ‘tigers’ in world exports of manufacturing ($ASIAEXP$). $\epsilon_t$ is a stochastic error, which almost certainly is positively auto-correlated given the overlapping nature of the dependent variable.

The first four lines of the equation capture both the dynamics and “equilibrium correction” mechanisms for four or more types of prices. Long run homogeneity is imposed through the ECMs. With one proviso, the long-run solution for log $PC$ is then a weighted average (weights adding to 1), of log $PPI$, log $ULC$, log $PIMP$, and log $OTHERP$, with the $X_t$ and trends as
potential shift factors in the relationship. The proviso is that the log level of the real exchange rate, defined as log domestic prices + log nominal trade weighted exchange rate – log trade weighted foreign price indices, contains the domestic consumer price index. However, long run homogeneity is still imposed, with log trade weighted foreign prices effectively also entering the long run solution for log $PC$.

Equation (1) does not explicitly include the non-linearities mentioned above. As discussed there, if the frequency of price change is state dependent, as in sticky information models such as that of Reis (2006), high recent rates of inflation could be associated with more rapid pass-through of inflation shocks. This might suggest that the parameters in equation (1), which incorporate the speed of adjustment, should vary with recent inflation experience. However, this would be a complex model, non-linear in both variables and parameters. A simpler model that captures some of the same ideas and possible asymmetries in price adjustment is to include additive terms of a non-linear transformation of recent changes in log prices. To be specific, for a basic specification, define the residual from the regression of the $(Δ_6\log PC)^2$ on a constant and on $Δ_6\log PC$ itself. This residual has the virtue of being orthogonal to the log change, so avoiding collinearity. It and its 6-month lag summarize the notion of non-linearities from recent inflation experience.

Sign priors for the main regressors are now discussed. As noted above, the equilibrium correction terms defined in equation (1) should all have positive coefficients. The log of the real exchange rate index should have a negative sign since the higher is the US Dollar relative to other currencies, and the lower are foreign prices, the cheaper are imports and the more difficult it is for domestic price setters to push through price increases. Among the X variables in equation (1), proxies for excess demand or the output gap should have a positive coefficient. Thus, the unemployment rate should have a negative coefficient. When its level is excluded, leading changes in the unemployment rate should have negative coefficients. Sign priors for other potential X variables are less clear cut. For example, real interest rates might be expected to have a negative effect on inflation, but this may already be reflected in excess demand proxies, and there is also the ‘cost channel’ of Barth and Ramey (2001). For example, mortgage interest rates feed into rents which are an important part of the consumer price deflator. Furthermore, if the Federal Reserve has information about future inflation not reflected elsewhere in the model, and raises interest rates to head off higher inflation, one might expect a positive coefficient on current interest rates.
Similar ambiguities surround the yield spread, defined as the yield on longer dated Treasury bonds, e.g. 3 or 10 years, minus the short rate, e.g. the 3-month T-bill rate. This could have an expectations interpretation through term-structure theory. A higher yield spread suggests that the market expects future short rates to rise relative to current rates in line with higher inflation expectations, see Fama (1990). However, the empirical evidence in Kozicki (1997) and De Bondt and Bange (1992), suggests that the yield spread is poor predictor for inflation and interest rate over one or two year horizons. Indeed, the term structure interpretation seems to rest on the idea that the private sector has better information than the central bank. However, there is evidence that the Fed’s Green Book forecasts are superior to those of the private sector, see Romer and Romer (2000). Also, the consensus is that consumer survey based measures of inflation expectations are not rational, and tend to lag inflation (see Roberts, 1997). If this is the case, a fall in the yield spread is likely to indicate a tightening of monetary policy reflecting the Fed’s anticipation of higher inflation in advance of the market. Then a positive coefficient on the yield spread might be expected in equation (1). Given the ambiguities, and more importantly, probable shifts in monetary policy, interest rates and spreads are omitted from this version of the paper.

For the trends, the decline in union density should be associated with lower inflation - hence a positive coefficient, while increased trade openness, and a rising share of Asian ‘tigers’ in world exports of manufactures would be expected to have a negative effect on inflation. However, these are all I(2) variables so that the risk of ‘spurious regression’ is considerable when some of the other variables in equation (1) are I(1) or I(0). Furthermore, the last two show acceleration over time and could potentially increase substantially further, though it seems implausible that US inflation would trend downwards limitlessly. Union density, on the other hand, effectively moves in an ogive from a high plateau to a low plateau, and can be thought of as a smooth version of a step dummy. A priori, union density seems the most likely candidate of the ‘trend’ variables for obtaining sensible results.

The above sign priors serve as a guide for selecting parsimonious models. However, no priors are imposed on price dynamics. Negative coefficients on lagged cost changes have several possible interpretations. For example, in the context of an ECM, they can indicate longer lags in the reaction of the consumer price index to costs. They can indicate the lagged effects of a policy response to inflation, or the negative effect on excess demand of lagged cost changes, for

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2 Data on union density and the Asian export share are interpolations of annual data so the tests are performed at an annual frequency.
example in the price of oil. They may also reflect a temporary squeeze in profit margins, followed by an inflationary restoration of margins.

A range of models of different levels of generality is examined, as outlined above, using BIC to select the maximum lag length (and sign priors in models including ECM terms). A check is carried on whether further reductions towards parsimony are helpful for forecasting, using automatic model selection in the form of Autometrics, Doornik (2008). This is an objective and easily reproducible tool, not affected by the subjective choices of the modeller, for a given data set. Any other investigator with the same data and the same specification of the ‘general unrestricted model’ (GUM), will then make the same model selection, given the chosen settings in Autometrics. This software examines a full set of general to simple reduction paths to select a parsimonious form of the GUM to satisfy a set of test criteria. The test criteria include tests for normality, heteroscedasticity, ARCH residuals, residual autocorrelation, parameter stability in the form of a Chow test, and the RESET test. There is also the option of automatically dummying out large outliers. In our context, the overlapping nature of the dependent variable means that residuals will be auto-correlated and so the corresponding tests, including portmanteau tests, are switched off. Further, outliers can easily arise, especially over 6 or 12-month horizons because of unpredictable changes in energy and other commodity prices. Heteroscedasticity could therefore be endemic. The corresponding tests are switched off also but use heteroscedasticity and autocorrelation corrected (HAC) t-ratios and F-tests for model selection.

Model selection given a GUM involves two potential errors: omitting relevant variables and including irrelevant variables. Heavy protection against the latter error results in smaller models being chosen. The default setting is chosen, limiting the probability to 0.05 of including an irrelevant variable, see Doornik (2008) for further details.

The alternative models are evaluated in terms of their pseudo out-of-sample forecasting performance based on root mean squared forecast error (RMSFE). Model selection takes place for monthly data running from January 1974 to December 1999. The reason for the January 1974 start (with a 12-month ahead inflation rate at January 1975) is to avoid some of the most volatile period of the first oil price shock, the collapse of Bretton Woods and the confusion of the Nixon price and wage controls. Forecasts are then run up to December 2007. For example, for the 12 month ahead inflation model, a form of equation (1) or its simpler variants, is run for data on the regressors from 1974(1) to 1998(12), meaning that the dependent variable runs to 1999(12).
From this model, the 12-month inflation rate for 2000(1) is forecast using data on the regressors up to 1999(1). Adding one month of data at a time, the forecasting equation and the forecasts are recursively updated, concluding with the 2006(12) forecast for the 2007(12) 12-month inflation rate. This generates 84 out of sample monthly forecast residuals.

The second oil shock in 1979-80, coinciding with large policy shocks, results in large outliers in all models. For all the 12-month ahead models therefore, dummies are include for the largest of these in the last month of 1978 and the first five months of 1979 (reflecting price shocks and dramatic shifts in monetary policy in 1979-80). All 12-month ahead models also incorporate dummies for the first three months of 1974, reflecting the aftermath of the removal of the Nixon price controls, see Frye and Gordon (1980) and Campbell and Duca (2006). Two dummies for hurricane Katerina\(^3\) are also included in all models.

### 3.2 Data issues

The \(PCE\) deflator \(PC\) is a chain-weighted index defined by

\[
\Delta \log PC_t = \sum_i w_i \Delta \log PC_{it}
\]

where \(w_i\) is the aggregate expenditure share of the ith good or service in month \(t\) and \(PC_{it}\) is its price. As noted above, it is chosen in preference to the CPI since the latter’s method of construction went through major shifts. Table 2 presents means and standard deviations of levels and changes of the main data used in the study, and indicates the order of integration of the data. Changes in log prices are I(0), while log levels are mostly I(1).

### 3.3 Results for the aggregate PC.

\(^3\) Hurricane Katerina caused fuel prices to spike in September and October 2005. We define an impulse dummy \(d\) in 2005:9. The 12-month lead of the 12-month change in this dummy, and its lag, would then capture the inflation effect seen in September and October 2005 if correctly anticipated in the 12-month ahead forecast made in September and October 2004. In recursive out of sample forecasting, we have no estimate of the coefficient on these dummies in 2004, so the surprise inflation of September-October 2005 shows up in the forecast errors. The advantage of including the dummies is that the dropping out of these effects 12 months later is captured in the forecasting model, mimicking real-time forecasting. Further, the precision of the parameter estimates of the models should improve by the inclusion of these dummies.
The discussion of the empirical results begins with ‘naïve’ autoregressive models in information set 1. Standard methodology is to use the Akaike or Schwarz information criterion to choose the lag length for the AR(k+1) process. We regress $\Delta_{12}\log PC_{i+12}$ on a constant, the above dummies, and $\Delta \log PC_i$, for i up to 24 months. Using this rudimentary form of model selection, we find k=5. The recursive out of sample RMSFE for 2000:1 to 2006:12 is 0.0095 shown in row 1, column 1 of Table 3. This would be the standard benchmark model used in the forecasting literature. It contrasts with 0.0088 for the unrestricted AR(24) model (not shown), suggesting that there is information in the longer inflation lags beyond k=5, which the information criterion does not pick up. However, in this paper’s approach of parsimoniously allowing longer lags to play a role, we regress $\Delta_{12}\log PC_{i+12}$ on a constant, the above dummies, and $\Delta \log PC_i$, $\Delta \log PC_{i-1}$, $\Delta_3 \log PC_i$, $\Delta_6 \log PC_i$, $\Delta_{12} \log PC_i$, and $\Delta_{12} \log PC_{i+12}$. The BIC criterion suggests dropping the last term. This results in an RMSFE of 0.0087, shown in row 1, column 3 of Table 3. We adopt this univariate PLL model as the naïve reference model for more sophisticated models, and also to check whether model averaging or ‘pooling’ forecasts is helpful for forecasting performance, as often reported in the literature.

Automatic model selection applied to the univariate PLL model suggests retaining only $\Delta \log PC_i$, $\Delta_6 \log PC_i$ and $\Delta_{12} \log PC_i$. Its RMSFE is also 0.0087, shown in row 1, column 5. We thus have prima facie evidence, albeit in a simple context, that the main gain in RMSFE relative to the AR(k+1) benchmark with k=5, comes from our PLL parameterisation (which also uses 5 parameters for lags but uses lags up to 12 months).

The information set is then sequentially expanded and the exercise repeated. Information set 2 of Table 3 adds a linear trend to the univariate autoregression: the RMSFE for the AR(5) model and our PLL variant are substantially worse, see row 2, columns 1 and 3. This corresponds to the intuition that the trend may be no friend for the forecaster - unbounded linear trends have implausible long-run implications. However, model averaging with the naïve reference model, see row 2, columns 2 and 4, restores performance close to that found when the linear trend is omitted. Here, automatic model selection helps forecast performance because it excludes the trend. Adding union density and changes in the unemployment rate, in place of a linear trend, in information set 3 tends to improve on the naïve reference model, particularly for the pooled

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4 This is equivalent to $\Delta \log PC_i$ for i=0,2, $\Delta_3 \log PC_i$, $\Delta_6 \log PC_i$, and $\Delta_{12} \log PC_i$, but tends to result in the choice of even more parsimonious models when model selection is introduced.
forecast. In information set 3A, we add the Asian export share, with little effect on the pooled forecasts, though the AR(k+1) and PLL based forecasts are a little worse.

The next extension of the data set is a major one: information set 4 introduces log changes in producer prices, hourly earnings, import prices, house prices, oil prices and the real exchange rate. This is the single equation reduced form of a VAR in these variables, plus changes in the unemployment rate, and the change in log $PC$. However, we retain union density as an additional regressor. The BIC criterion now selects $k=2$ and the RMSFE is shown in column 1. Clearly, the 6 x k extra parameters weigh heavily in BIC, relatively to the improvement in fit they bring. The RMSFE is a little better than for the simple AR(6) specification and the pooled forecasts are also notably better than in row 1. However, our more parsimonious parameterisation now brings a substantial improvement both for the standard and the pooled forecast, columns 3 and 4. Automatic model selection is unhelpful here, though forecast pooling again protects performance.

Adding the Asian export share in information set 4A, brings a severe deterioration in forecast performance, though forecast pooling again protects against the worst consequences. Clearly and not surprisingly, the unlimited nature of the non-linear trend represented by the Asian export share is a danger for forecasting. Automatic model selection provides no protection against these dangers, as columns 5 and 6 for information set 4A reveal.

Information set 5 adds the ECM terms to information set 4 (which includes union density, but not the Asian export share). Several ECM terms have the wrong sign (oil and import prices) and are excluded. Leading changes in the unemployment rate have positive (though not very significant) coefficients in the PLL specification in column 3 and are omitted, leaving $\Delta_6\text{UNR}_{t-6}$ and $\Delta_{12}\text{UNR}_{t-12}$ as the included terms. Forecast performance deteriorates somewhat relative to information set 4 though is still substantially better than for the information sets 1 to 3 (including the naïve reference model). Automatic model selection has relatively neutral consequences here. On the face of it, the trending nature of the ECM terms looks problematic, in that there may be structural breaks in their trends. Adding the level of the unemployment rate to the information set in 5A, brings marginal improvements, most evident in the pooled forecasts.

The next extension to the information set brings substantial improvements: information set 6 adds the non-linearity in recent inflation, SQRES, i.e. the residual from the squared value of $\Delta_t \log PC_t$ as defined above, and its 6 month lag. This improves the RMSFEs quite strikingly, particularly
for the PLL version, and as ever, for its pooled forecast version. Automatic model selection improves marginally in its pooled forecast version, cf. column 6 and column 4. Clearly, the non-linearities, which are highly significant over the estimation period, have important information content. This is consistent with state-dependent pricing rather than Calvo-style price setting. Extending the information set in 6A to include the level of the unemployment rate is relatively neutral for the AR(k) and general PLL versions of the model, but causes some deterioration when automatic model selection is applied.

In information set 6B, the sign restrictions on the ECMs in oil and import prices and leading changes in the unemployment rate are relaxed; the effects are somewhat mixed. For the PLL specification and its model selected version, the standard forecasts are worse. The pooled forecasts for the general PLL model improve a little while those for the model selected version deteriorate notably.

Finally, consider an extension of the PLL parameterisation incorporating some moving average formulations. This takes 12-month moving averages of the log real exchange rate and the ECM terms are defined by \([\text{ma12log } PC_t - \log PC_t]\). This formulation was inspired by noting the pronounced negative \(\Delta_3, \Delta_6\) and \(\Delta_{12}\) effects corresponding to most ECM terms, consistent with a backward shift in the average lag. For changes in the unemployment rate and the log real exchange rate, we use 3-month moving averages: \(\Delta_3\text{ma3X}_t, \Delta_6\text{ma3X}_t, \Delta_{12}\text{ma3X}_t, \text{and } \Delta_{12}\text{ma3X}_{t-12}\). Effectively this averages monthly data to a quarterly frequency, and saves two parameters for each variable. With the sign restrictions again imposed, union density and the squared terms included, we now achieve an RMSFE of 0.0056, the best of the models considered so far. The pooled forecast version now shows a slight deterioration with an RMSFE of 0.0057. This model also has the best BIC for the 1974-1999 sample of all models considered. Automatic model selection here causes some deterioration in forecast performance, though forecast pooling offers substantial protection.

The general points that emerge are as follows: first, our parsimonious longer lag (PLL) specification outperforms the AR(k+1) or VAR(k+1) alternative, where BIC is used to select the lag length k, in almost all comparisons. This suggests that PLL offers a powerful practical tool for overcoming the curse of dimensionality suffered by VAR models in modelling and forecasting contexts. Secondly, in almost all comparisons, model averaging or pooling of the more sophisticated model with a naïve reference model outperforms the forecasts from the more
sophisticated model. Unsurprisingly, the worse the sophisticated model, the more dramatic is the benefit of pooling. In the only case where pooling did not help, the cost was small: raising RMSFE from 0.0056 to 0.0057. This suggests that the robustness benefits from pooling are considerable and that it should generally be used. Thirdly, there is useful information in lagged changes in log PPI, log earnings, log import prices, log oil prices, log house prices and the log real exchange rate for forecasting the consumer expenditure deflator. Fourthly, there is powerful evidence that non-linearities in the inflation process improve forecasting performance, when combined with equilibrium correction specifications of key drivers. Finally, automatic model selection has mixed outcomes for forecast performance: the benefits tend to be small, but more often there is a slight deterioration in forecast performance, and occasionally a more noticeable deterioration. In other words, basic GUM design appears to be more important than the use of model selection, once the GUM has been chosen. However, frequent reselection of a parsimonious model is likely to bring forecasting benefits.

The selection of more parsimonious models with Autometrics has two potential advantages if there is little structural change. One is that parameter estimation uncertainty is reduced in more parsimonious representations consistent with the underlying data generating process. Lower estimation uncertainty should lower the forecast error variance. The second is that the selected models pass several specification tests over the estimation period, of which the Chow test for parameter stability is the most important. This reduces the risk of selecting well-fitting but unstable models. However, if there is a structural break in the forecast period, a more parsimonious model may forecast less well since the more general model has more variables whose parameters can shift as the sample is updated recursively, to respond to the structural break. It is also possible that because of data collinearities in the estimation period, automatic model selection can exclude relevant variables. If adding further observations resolves such collinearities, a more general model may forecast better. Structural breaks and unresolved collinearities are plausible explanations for the tendency reported in Table 3 for the GUMs often to forecast better than the more parsimonious selected models.

4. Empirical results for the indirect approach.

A major objective of this paper is to examine the performance of models which forecast the main components of the \textit{PCE} deflator separately and then weight these forecasts to produce a forecast
for the overall index. A similar investigative strategy to that set out in Table 3 is followed. In the sectoral version of equation (1), \( PC \) is respectively replaced by \( PDG \), \( PND \) and \( PSS \), the price indices for durable goods, non-durable goods and services, respectively. The \( OTHERP \) category is expanded to include \( PC \) and some sector-specific PPIs. Results are first discussed for naïve models using lags in the own inflation rates respectively for the overall price index, the durables component, the non-durable goods component and for services. Then the information set is extended to include for each component the aggregate indicators used in Section 3, augmented by sector-specific PPI indices, first without ECMs and level variables and then including them. Table 4 reports the results in the absence of automatic model selection.

For naïve models based on AR(k+1) specifications, the BIC criterion chooses \( k=4 \) for durable goods, \( k=5 \) for non-durables and \( k=6 \) for services. Row 1 of Table 4 shows that weighting the naïve component forecasts to produce the ‘indirect’ 12 month ahead forecast for the PC deflator substantially improves on the performance of the direct forecast. However, forecast pooling with the naïve reference model for aggregate log \( PC \) used in Section 3, marginally worsens the RMSFE. Row 2, corresponding to the parsimonious longer lags (PLL) version of information set 1, shows that when we replace AR(k+1) with our parsimonious method for introducing longer lags, both direct and indirect models improve further, with the indirect forecasts again substantially better than the direct.

In information set 2, we add a linear trend to each model: forecast performance deteriorates sharply, though forecast pooling protects substantially. In information set 3, we replace the linear trend by union density and changes in the unemployment rate. This has significant benefits, particularly with forecast pooling, and again the indirect method beats the direct single equation forecasts.

Information set 4 brings a major expansion in the information set: we introduce changes in log \( PPI \) and some sectoral PPIs, log \( EARN \), log \( REER \), log \( PIMP \), as well as in log \( PC \) and in the unemployment rate. The sectoral PPIs chosen for durable consumer goods are for durable manufacturing and miscellaneous manufacturing, and for non-durable consumer goods are for non-durable manufacturing, processed food manufacturing, miscellaneous manufacturing and maize prices. The BIC criterion selects 2 as the maximum lag length for all components and for the aggregate index. But the benefits from this extension of the information set are marginal.
relative to information set 3, though the pooled version of the indirect method again beats the direct.

The next extension, in information set 5, is to include ECM terms and the level of the log real exchange rate. Applying sign priors so that all included ECM terms have non-negative coefficients, and that leading terms in the change the unemployment rate have non-positive coefficients, results in the exclusion of a number of variables. Linear trends are included in the durables and services equations, given the trends in their prices relative to log PC, but not in the non-durables equation. Once again the indirect method outperforms the direct method and forecast pooling is very helpful.

Information set 6 adds the non-linear terms (found so successful in the previous section) for forecasting log $PC$. They are significant in every equation and further improve forecast performance. However, the improvement is most pronounced at the aggregate level, where the RMSFE for the pooled direct forecast is down to 0.0063, by comparison with 0.0069 for the pooled indirect forecast.

Finally, information set 7 uses 12-month moving average versions of the ECMs and of the log real exchange rate, and changes in 3-month moving averages of the unemployment rate and the log real exchange rate. As we know from Table 3, this produces the best forecast forecasting performance among alternative direct forecasts for log $PC$. It also improves the indirect pooled forecasts, but they now under-perform relatively to the direct single equation forecasts.

Next, the question of whether automatic model selection helps is addressed. Table 5 shows corresponding results which can be compared with Table 4. Using the pooled indirect forecasts as the criterion, model selection does better in two out of seven information sets and worse in five. The ranking of the indirect pooled forecasts relative to direct pooled forecasts is the same as in Table 4: in the first five information sets, the indirect beats the direct, but the opposite holds true in the last two information sets. For all indirect forecasts except for the univariate AR(k), forecast pooling improves performance.

To summarise, though the indirect method fails to beat the direct method for the last two information sets, it nevertheless looks promising. It seems plausible that sector specific additions in information will improve the sectoral price forecasts and thereby the constructed overall
forecasts of the $PCE$ deflator. One class of candidates for consideration is sector-specific non-linearities. Another area to look for improvements is in the measurement of sectoral unit labour costs. The BLS does not publish data on service sector unit labour costs, perhaps because the productivity or output data on the service sector are less well measured than for the rest of the economy. However, it may be possible to obtain proxies from other sources. The fact that we used only whole economy private sector unit labour costs in the components as well as the aggregate inflation models tends to favour forecasts for the aggregate log $PC$ relative to forecasts for its components.

In terms of the economic content of the different forecasting equations, the aggregate log $PC$ equation in information set 7 has five level effects: these are for union density, the log real exchange rate, and ECMs in unit labour costs, house prices and the overall $PPI$. Lagged changes in unemployment rates, non-linear inflation terms and various changes in log prices for oil, imports etc. also appear. For the durables equation, there are five level effects: a linear trend, the log real exchange rate (which has a particularly powerful effect for durables) and ECMs in unit labour costs, in the $PPI$ for miscellaneous goods and in house prices. In addition to the dynamic terms mentioned for the overall log $PC$ equation, changes in log prices for durable and miscellaneous manufacturing also appear. For the non-durables equation, there are also five level effects: these are union density, the log real exchange rate, and ECMs in unit labour costs, and $PPI$s for processed food and miscellaneous manufacturing. The dynamic terms also include log changes in $PPI$s corresponding to the ECMs and for non-durable manufacturing and maize prices.

Finally, the service sector price equation contains six level effects: these are a linear trend, union density, ECMs in unit labour costs, house prices, import prices and in overall $PC$. This is the only sector where the level log $PC$ appears in an ECM (signs are negative in the other sectors), providing evidence that service sector prices lag behind the aggregate $PCE$ deflator. The log real exchange rate does not appear, consistent with the broadly non-tradeable character of the service sector. The dynamic terms include the same set of variables as in the aggregate log $PC$ equation since there are no sector-specific $PPI$s for services.

Though an ECM in oil prices was included in every initial general unrestricted model both at the aggregate and the sectoral level, its sign was always negative and this ECM term was therefore excluded throughout. Dynamics in oil prices are, however, usually significant.
ECMs in house prices appear in all equations, though they are weakest in the durables equation, where the real exchange rate effect is stronger than in other sectors. The lag structures always suggest quite long lags in the transmission of house prices to sectoral prices and overall $PC$. It is unclear in this kind of reduced form whether the house price effect is mainly a rent or cost effect (for example on business costs through the correlation between land prices and business rents) or also captures economic activity related to housing collateral or wealth effects on consumer expenditure. However, the models are consistent with powerful monetary policy effects on inflation in the US given the influence of monetary policy on the exchange rate, house prices and the unemployment rate.

5. Conclusions

For the US, monthly models are estimated over 1974-1999 for the personal consumption expenditure deflator ($PC$), the price index preferred by the Federal Reserve, and its three main sub-components, non-durable goods, durables and services. Inflation is then forecast 12 months ahead, up to the end of 2007, updating the estimated model by one month every time the forecasts move one month forward (i.e. recursive forecasting). This process attempts to replicate what forecasters might have done in real time. Since data revisions for all the variables included in this exercise tend to be relatively small, the results should be close to genuine real time forecasting.

The literature on inflation forecasting agrees that simple autoregressive models are hard to beat. The paper demonstrates substantial out-performance against simple benchmark models in a variety of information sets. A key innovation is to use parsimonious longer lags (PLL) in place of the standard AR or VAR approach with a lag length of $k+1$ months, where $k$ is chosen by the use of an information criterion. For data in differences, PLL uses the 12-month change at a 12-month lag, the 6-month change at a lag of 6 months, the 3-month change at a lag of 3 months, and unrestricted monthly lags for the first three months. For the aggregate log $PC$ equations, Section 3 demonstrated that in almost every information set, the PLL specification produces better forecasts than the AR($k+1$) or VAR($k+1$) approach. This suggests that standard VAR methods tend to omit relevant longer lags. Further evidence is provided for the often-reported finding in the forecasting literature that forecast pooling or averaging improves forecast performance. In particular, the simple averaging of a naïve forecast based on univariate data and a more sophisticated model almost always outperforms both the sophisticated and the naïve model.
The paper demonstrates the usefulness of information on oil prices, producer price indices, hourly earnings, the real exchange rate, import prices, house prices, and changes in the unemployment rate for forecasting PC inflation. The combination of equilibrium correction terms, which bring gradual adjustment of relative prices into the inflation process, and non-linearities, was shown to contribute importantly to out-performance relative to the benchmark model. It is possible that these factors account for important parts of the drift in the univariate inflation process for the US, reported by Stock and Watson (2006).

Some of the potential pitfalls of forecasting are illustrated by incorporating a linear trend and, even worse, the export share of Asian ‘tiger’ economies, in some of the models. Unbounded trends have implausible implications for inflation rates in the long run, and examples of poor pseudo out of sample forecasting performance are reported when such trends are included in equations for \( \log PC \). Including the level of the unemployment rate can also lead to a more moderate deterioration in forecast performance in some contexts. The literature on time variations in the natural rate of unemployment warns of this possibility.

Durable goods, non-durable goods and services have very different inflation histories. Therefore gains might be expected from sectoral information. The relative price of durables has declined for four decades, while the relative price of services has risen for three decades. The estimated models find strong evidence for sectoral equilibrium correction relationships formulated for relative price levels, with important implications for future inflation trends. The paper explored potential improvements from an indirect forecast via weighted sub-component forecasts versus a direct forecast of the aggregate price index. Once again, the average of the sophisticated and the univariate autoregressive benchmark models substantially outperforms each. The findings reported in Section 4 suggest that for five out of seven information sets considered, the indirect method outperforms the direct method. As for the aggregate model, highly significant evidence is found for the relevance of non-linearities at the sectoral level: higher recent inflation disproportionately raises inflation over the next 6 or 12 months. Exploring idiosyncratic sectoral non-linearities is an important topic for future work and is likely to improve the power of the indirect forecasting approach further.

Another issue concerning forecasting methodology explored at both the aggregate and the sectoral level is whether model selection improves performance. Automatic model selection
using Doornik (2008) Autometrics was used to select parsimonious models from general unrestricted models (GUMs). The evidence proves to be somewhat mixed, but more negative than positive: the gains from selection are usually small, but in several instances the deterioration of forecast performance is notable. It is likely that less restricted models are better able to handle structural breaks and the resolution of previous multi-collinearities. However, the test posed in this paper for the automatic selection method is tougher than real time forecasters actually face. In the paper, model selection takes place just once – for the 1974 to 1998 sample. In practice, real time forecasters could reselect the parsimonious model on a rolling monthly basis, allowing the model to react far better to structural breaks and other new information on the parameters.

To draw out some of the wider economic implications, the models estimated are consistent with strong monetary policy impacts on inflation, working through the real exchange rate, house prices and changes in the unemployment rate. Unit labour costs are important not only at the aggregate level, but in each of the sub-components equations, but the feed-through to overall inflation is quite slow. The feed-through from house prices is even slower. Forecast errors are clearly associated with unpredictable shocks to oil and raw food prices. Given the important roles in the models of unit labour costs and their moderation in 2008, the important role of US house prices and their falls, the unwinding of the oil and food price rises of 2008 is likely to results in far lower inflation rates in 2009.

Our work also throws modest light on the causes of the reduction since the early 1980s in inflation and in its volatility (the ‘great moderation’, Bernanke (2004)). Our key findings are two: the first is that the decline in union density has a significant negative effect on inflation in most specifications. The second is consistent with an element of the ‘luck’ hypothesis: strong evidence of non-linearities in the inflation process suggests anything that reduces inflation will tend to keep inflation down, and recent lower inflation volatility is associated with lower inflation to come.

References


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Source: compiled by authors.
Table 2: Statistics and Variable Definitions: 1974:1-2007:12

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<td>Log PC</td>
<td>Log of consumer expenditure deflator</td>
<td>4.29</td>
<td>0.354</td>
<td>-3.69*</td>
<td>-5.90**</td>
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<td>Log PDG</td>
<td>Log of the “durables goods” sub-component</td>
<td>4.52</td>
<td>0.174</td>
<td>-3.55*</td>
<td>-7.96**</td>
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<td>Log PND</td>
<td>Log of the “non-durables goods” sub-component</td>
<td>4.33</td>
<td>0.298</td>
<td>-3.90*</td>
<td>-9.51**</td>
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<td>Log PSS</td>
<td>Log of the “services” sub-component</td>
<td>4.20</td>
<td>0.441</td>
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<td>Log POIL</td>
<td>Log of West Texas Intermediate crude oil price</td>
<td>3.12</td>
<td>0.423</td>
<td>-1.71</td>
<td>-16.9**</td>
</tr>
<tr>
<td>Log REER</td>
<td>Log of the real effective exchange rate (uses consumer price indices for trading partners to deflate nominal effective exchange rate)</td>
<td>4.55</td>
<td>0.098</td>
<td>-1.96</td>
<td>-14.8**</td>
</tr>
<tr>
<td>Log PIMP</td>
<td>Log of non-petroleum import prices</td>
<td>4.56</td>
<td>0.173</td>
<td>-3.08</td>
<td>-4.75**</td>
</tr>
<tr>
<td>Log HP</td>
<td>Log of median existing US house prices</td>
<td>11.6</td>
<td>0.515</td>
<td>-2.35</td>
<td>-21.0**</td>
</tr>
<tr>
<td>Log ULC</td>
<td>Log of unit labour costs in non-agric. private sector (monthly interpolation of quarterly data)</td>
<td>4.46</td>
<td>0.303</td>
<td>-3.55*</td>
<td>-5.37**</td>
</tr>
<tr>
<td>Log HEPRIV</td>
<td>Log of hourly earnings in non-agric. private sector</td>
<td>2.27</td>
<td>0.370</td>
<td>-3.94*</td>
<td>-4.81**</td>
</tr>
<tr>
<td>Log PPIALL</td>
<td>Log of wholesale price for total domestic goods</td>
<td>4.66</td>
<td>0.280</td>
<td>-3.64*</td>
<td>-8.33**</td>
</tr>
<tr>
<td>Log PPIMISC</td>
<td>Log of wholesale price for miscellaneous goods</td>
<td>4.71</td>
<td>0.314</td>
<td>-2.68</td>
<td>-8.55**</td>
</tr>
<tr>
<td>Log PPIDUR</td>
<td>Log of the wholesale price for durable manufactured goods</td>
<td>4.69</td>
<td>0.272</td>
<td>4.50**</td>
<td>-5.56**</td>
</tr>
<tr>
<td>Log PMAIZE</td>
<td>Log of the price of US maize (Chicago)</td>
<td>4.69</td>
<td>0.180</td>
<td>-3.76*</td>
<td>-10.2**</td>
</tr>
<tr>
<td>Log PPIFOOD</td>
<td>Log of the wholesale price for processed food</td>
<td>4.72</td>
<td>0.228</td>
<td>-3.21</td>
<td>-12.8**</td>
</tr>
<tr>
<td>UNDENS</td>
<td>Union density, 12-month moving average</td>
<td>13.8</td>
<td>4.99</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>ASIAEXP</td>
<td>Share in World manufactured exports of Asian economies (excl. Japan, Israel), 12-month moving average of annual interpolated data</td>
<td>5.27</td>
<td>2.69</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>ROPENMA12</td>
<td>Conventional trade policy measure in real terms: ratio of real exports plus real imports to real GDP, 12-month moving average of monthly data</td>
<td>134</td>
<td>42.9</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>UNR</td>
<td>Unemployment rate for those aged 25 or over (%)</td>
<td>4.75</td>
<td>1.12</td>
<td>-3.43*</td>
<td>-7.18**</td>
</tr>
</tbody>
</table>

Source: Data from BEA (US), BLS (US), BIS, BP, IFS (International Monetary Fund), US Census Bureau, UN Monthly Digest, FRED and Dallas Federal Reserve Bank. Statistics are reported to three significant figures.

a. For a variable X, the augmented Dickey-Fuller (1981) statistic is the t ratio on \( \pi \) from the regression:
\[
\Delta X_t = \pi X_{t-1} + \sum_{i=1}^{k} \theta_i \Delta X_{t-i} + \psi_0 + \psi_1 t + \epsilon_t,
\]
where k is the number of lags on the dependent variable, \( \psi_0 \) is a constant term, and t is a trend. The kth-order augmented Dickey-Fuller statistic is reported, where k is the last significant lag of the 3 lags employed. The trend is included if significant. For null order I(2), \( \Delta X \) replaces X in the equation above. Critical values are obtained from MacKinnon (1991). Asterisks * and ** denote rejection at 5% and 1% critical values. Stationarity tests are performed for the variables in levels before time-transformation.

b. For several price level variables the test statistics are based on the inclusion of a time trend, though this is not strictly significant. If the trend is excluded, the test would suggest they are I(0) but with an implausibly low speed of adjustment (less than 1 percent).
Table 3: Root mean square 12 months ahead forecast errors for the aggregate price index comparing different information sets and methods.

<table>
<thead>
<tr>
<th>Info Set 1</th>
<th>AR(k)</th>
<th>Average of AR(k) and naïve PLL model*</th>
<th>Parsimonious longer lags GUMs</th>
<th>Average of PLL GUMs models and naïve PLL model*</th>
<th>Parsimonious longer lags with automatic model selection</th>
<th>Average of column 4 and naïve model forecasts</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.0095</td>
<td>0.0091</td>
<td>0.0087</td>
<td>0.0087</td>
<td>0.0087</td>
<td>0.0087</td>
</tr>
<tr>
<td></td>
<td>0.0109</td>
<td>0.0087</td>
<td>0.0107</td>
<td>0.0088</td>
<td>0.0087</td>
<td>0.0087</td>
</tr>
<tr>
<td></td>
<td>0.0094</td>
<td>0.0084</td>
<td>0.0097</td>
<td>0.0085</td>
<td>0.0099</td>
<td>0.0086</td>
</tr>
<tr>
<td></td>
<td>0.0097</td>
<td>0.0084</td>
<td>0.0099</td>
<td>0.0085</td>
<td>0.0099</td>
<td>0.0085</td>
</tr>
<tr>
<td></td>
<td>0.0089</td>
<td>0.0080</td>
<td>0.0078</td>
<td>0.0077</td>
<td>0.0085</td>
<td>0.0079</td>
</tr>
<tr>
<td></td>
<td>0.0122</td>
<td>0.0089</td>
<td>0.0113</td>
<td>0.0087</td>
<td>0.0149</td>
<td>0.0099</td>
</tr>
<tr>
<td></td>
<td>0.0106</td>
<td>0.0084</td>
<td>0.0099</td>
<td>0.0080</td>
<td>0.0097</td>
<td>0.0081</td>
</tr>
<tr>
<td></td>
<td>0.0098</td>
<td>0.0082</td>
<td>0.0094</td>
<td>0.0079</td>
<td>0.0101</td>
<td>0.0080</td>
</tr>
<tr>
<td></td>
<td>0.0093</td>
<td>0.0074</td>
<td>0.0070</td>
<td>0.0063</td>
<td>0.0074</td>
<td>0.0062</td>
</tr>
<tr>
<td></td>
<td>0.0088</td>
<td>0.0073</td>
<td>0.0070</td>
<td>0.0064</td>
<td>0.0094</td>
<td>0.0071</td>
</tr>
<tr>
<td></td>
<td>0.0086</td>
<td>0.0072</td>
<td>0.0079</td>
<td>0.0061</td>
<td>0.0094</td>
<td>0.0069</td>
</tr>
<tr>
<td></td>
<td>0.0108</td>
<td>0.0078</td>
<td>0.0056</td>
<td>0.0057</td>
<td>0.0083</td>
<td>0.0061</td>
</tr>
</tbody>
</table>

Notes:
1. Variable definitions are in Table 2.
2. Info sets are:
   - Info Set 1: 1974 and 1979 dummies, constant and lags in Δ log PC
   - Info Set 2: Set 1 plus linear trend
   - Info Set 3: Set 1 plus UNDENS and changes in unemployment rate, Δ UNR
   - Info Set 3A: Set 3 plus ASIAEXP
   - Info Set 4: Set 3 plus changes in log PPI, log EARN, log REER, log PIMP, log HP and log PC
   - Info Set 4A: Set 4 plus ASIAEXP
   - Info Set 5: Set 4 plus ECM terms and level log REER (with sign restrictions)
   - Info Set 5A: Set 5 plus unemployment rate level, UNR
   - Info Set 6: Set 5 plus squared terms
   - Info Set 6A: Set 6 plus UNR
   - Info Set 6B: Set 6 without sign restrictions
   - Info Set 7: Set 6 using MA12 in ECM terms and level log REER and MA3 in Δ log REER and Δ UNR terms (with sign restrictions)

* Parsimonious longer lags (PLL model) for variable Z are defined by ΔZ₁, ΔZ₁₋₁, Δ₃Z₁, Δ₆Z₁, Δ₁₂Z₁, and Δ₁₂Z₁₋₁₂, except for Δ₈UNR, which is replaced by Δ₃UNR₈₋₃ and Δ₁₂UNR, which is replaced by Δ₈UNR₈₋₆.
Table 4: Root mean square 12 months ahead forecast errors for the aggregate price index, the three component group price index forecasts, and the aggregated weighted component group (indirect) forecasts.

<table>
<thead>
<tr>
<th></th>
<th>$\Delta_{12}\log PDG$</th>
<th>$\Delta_{12}\log PND$</th>
<th>$\Delta_{12}\log PSS$</th>
<th>$\Delta_{12}\log PC-IND POOLED$</th>
<th>$\Delta_{12}\log PC-DIRECT POOLED$</th>
<th>$\Delta_{12}\log PC-DIRECT POOLED$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Durable goods</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Non-durable goods</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Services</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Indirect aggregate sub-components forecast</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Indirect aggregate sub-components forecast pooled with naïve forecast</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Direct aggregate forecast</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Direct aggregate forecast pooled with naïve forecast</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>


| Info Set 1 | 0.0145 | 0.0220 | 0.0062 | 0.0080 | 0.0083 | 0.0095 | 0.0091 |
| Info Set 1 | 0.0127 | 0.0202 | 0.0055 | 0.0073 | 0.0079 | 0.0087 | 0.0087 |
| Info Set 2 | 0.0155 | 0.0219 | 0.0079 | 0.0105 | 0.0083 | 0.0107 | 0.0088 |
| Info Set 3 | 0.0125 | 0.0216 | 0.0053 | 0.0083 | 0.0078 | 0.0097 | 0.0085 |
| Info Set 4 | 0.0139 | 0.0198 | 0.0072 | 0.0082 | 0.0076 | 0.0078 | 0.0077 |
| Info Set 5 | 0.0200 | 0.0185 | 0.0084 | 0.0088 | 0.0074 | 0.0099 | 0.0080 |
| Info Set 6 | 0.0178 | 0.0207 | 0.0081 | 0.0095 | 0.0069 | 0.0069 | 0.0063 |
| Info Set 7 | 0.0134 | 0.0201 | 0.0079 | 0.0087 | 0.0066 | 0.0056 | 0.0057 |

Notes:
1. Variable definitions are in Table 2.
2. Info sets are:
   - Info Set 1: AR(k): 1974 and 1979 dummies, constant and lags in $\Delta\log PC$, AR(k+1) specification with k=5 for $\log PC$, k=4 for durable goods, k=5 for non-durables and k=6 for services
   - Info Set 1: 1974 and 1979 dummies, constant and lags in $\Delta\log PC$, parsimonious longer lags*
   - Info Set 2: Set 1 plus linear trend in all equations
   - Info Set 3: Set 2 plus UNDENS and UNR terms (with sign restrictions), no linear trend in $\Delta\log PC$ and non-durables equation since not significant
   - Info Set 4: Set 3 plus changes in sector-specific log PPIs, log EARN, log REER, log PIMP, log HP and in $\Delta\log PC$, with parsimonious longer lags*
   - Info Set 5: Set 4 plus ECM terms and level log REER (with sign restrictions).
   - Info Set 6: Set 5 plus squared terms.
   - Info Set 7: Set 6 using MA12 in ECM terms and level log REER and MA3 in $\Delta\log REER$ and UNR terms (with sign restrictions)

*Parsimonious longer lags for variable Z are defined by $\Delta Z_t$, $\Delta Z_{t-1}$, $\Delta Z_{t-3}$, $\Delta Z_{t-4}$, $\Delta Z_{t-12}$, except for $\Delta Z_{t} UNR_t$ which is replaced by $\Delta Z_{t} UNR_{t-3}$ and $\Delta Z_{t} UNR_{t}$ which is replaced by $\Delta Z_{t} UNR_{t-6}$.  


Table 5: Root mean square 12 months ahead forecast errors for the aggregate price index, the three component group price index forecasts, and the aggregated weighted component group (indirect) forecasts using Autometrics model selection.

<table>
<thead>
<tr>
<th></th>
<th>$\Delta_{12}\log\text{PDG}$</th>
<th>$\Delta_{12}\log\text{PND}$</th>
<th>$\Delta_{12}\log\text{PSS}$</th>
<th>$\Delta_{12}\log\text{PC-IND}$</th>
<th>$\Delta_{12}\log\text{PC-IND POOLED}$</th>
<th>Estimation period 1974:1-1998:12, then recursive forecasts for 12-month ahead change from 2000:1 to 2006:12</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Durable goods</td>
<td>Non-durable goods</td>
<td>Services</td>
<td>Indirect aggregate sub-components forecast</td>
<td>Indirect aggregate sub-components forecast pooled with naïve forecast</td>
<td>Direct aggregate forecast</td>
</tr>
<tr>
<td>Info Set 1</td>
<td>0.0128</td>
<td>0.0210</td>
<td>0.0054</td>
<td>0.0075</td>
<td>0.0080</td>
<td>0.0087</td>
</tr>
<tr>
<td>Info Set 2</td>
<td>0.0155</td>
<td>0.0248</td>
<td>0.0082</td>
<td>0.0117</td>
<td>0.0087</td>
<td>0.0118</td>
</tr>
<tr>
<td>Info Set 3</td>
<td>0.0114</td>
<td>0.0231</td>
<td>0.0078</td>
<td>0.0104</td>
<td>0.0084</td>
<td>0.0099</td>
</tr>
<tr>
<td>Info Set 4</td>
<td>0.0102</td>
<td>0.0230</td>
<td>0.0079</td>
<td>0.0090</td>
<td>0.0078</td>
<td>0.0085</td>
</tr>
<tr>
<td>Info Set 5</td>
<td>0.0148</td>
<td>0.0173</td>
<td>0.0105</td>
<td>0.0094</td>
<td>0.0072</td>
<td>0.0097</td>
</tr>
<tr>
<td>Info Set 6</td>
<td>0.0160</td>
<td>0.0202</td>
<td>0.0094</td>
<td>0.0100</td>
<td>0.0073</td>
<td>0.0074</td>
</tr>
<tr>
<td>Info Set 7</td>
<td>0.0110</td>
<td>0.0224</td>
<td>0.0079</td>
<td>0.0107</td>
<td>0.0074</td>
<td>0.0083</td>
</tr>
</tbody>
</table>

Notes:
1. Variable definitions are in Table 2.
2. Info sets are:
   - Info Set 1: 1974 and 1979 dummies, constant and lags in $\Delta\log PC$, AR(k+1) specification with k=5 for $\log PC$, k=4 for durable goods, k=5 for non-durables and k=6 for services
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   - Info Set 3: Set 2 plus linear trend in all equations
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   - Info Set 5: Set 4 plus changes in $\log PPI$, $\log EARN$, $\log REER$, $\log PIMP$, log house prices and in $\log PC$, with parsimonious longer lags*
   - Info Set 6: Set 5 plus ECM terms and level log $REER$ (with sign restrictions)
   - Info Set 7: Set 6 plus squared terms
   - Info Set 8: Set 7 using MA12 in ECM terms and level log $REER$ and MA3 in $\Delta\log REER$ and $\Delta UNR$ terms (with sign restrictions)

* Parsimonious longer lags for variable Z are defined by $\Delta Z_t$, $\Delta Z_{t-1}$, $\Delta^2 Z_t$, $\Delta Z_{t-1}$, $\Delta^2 Z_{t-1}$, and $\Delta^3 Z_{t-12}$, except for $\Delta_4 UNR_t$ which is replaced by $\Delta_3 UNR_{t+3}$ and $\Delta_1 UNR_{t+6}$.
Figure 1: Log relative prices for durables, non-durables and services

Figure 2: Weights (expenditure shares) of durable goods, non-durable goods and services.
Figure 3: PC aggregate and subindices (in logarithms)

Figure 4: First differences of PC aggregate and subindices (in logarithms)
Figure 5: Twelfth differences of PC aggregate and subindices (in logarithms)

Figure 6: Union density, the export share of Asian ‘tigers’, real trade openness and unemployment

Note: Definitions are in Table 2