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ABSTRACT

Does aggregating forecasts by CPI component improve inflation forecast accuracy in South Africa?*

Inflation is a far from homogeneous phenomenon, a fact often neglected in modelling consumer price inflation. This study, the first of its kind for an emerging market country, investigates gains to inflation forecast accuracy by aggregating weighted forecasts of the sub-component price indices, versus forecasting the aggregate consumer price index itself. Rich multivariate equilibrium correction models employ general and sectoral information for ten sub-components, taking account of structural breaks and institutional changes. Model selection is over 1979-2003, with pseudo out-of-sample forecasts, four-quarters-ahead, generated to 2007. Aggregating the weighted forecasts of the sub-components does outperform the aggregate CPI forecasts, and also offers substantial gains over forecasting using benchmark naïve models. The analysis also contributes an improved understanding of sectoral inflationary pressures. This forecasting method should be more robust to the regular reweighting of the CPI index.

JEL Classification: C22, C32, C51, C52, C53, E31 and E52
Keywords: CPI sub-components, disaggregation, error correction models, evaluating forecasts, model selection, multivariate time series and sectoral inflation

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1. Introduction

As the popularity of inflation targeting has spread, inflation forecasting has come to play a central element in economic policy-making. Several emerging market and developing economies have adopted inflation targeting since the 1990s, including South Africa in 2000. In practice, a range of approaches is used to forecast inflation. Most inflation models forecast the total price index, e.g. the consumer price index. 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 projected ahead, often using fairly crude methods. Until recently, the two approaches were rarely combined, though Bryan and Cecchetti (1999) examined the relationship between overall inflation and changes in the sub-components of the consumer price index (CPI). In this paper, we span the two approaches for an emerging market country, South Africa (SA).

There has been renewed interest in investigating whether there are gains to forecast accuracy in aggregating weighted forecasts of the sub-component price indices, as against forecasting the aggregate itself (e.g. Hubrich, 2005). 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 e.g., technological innovation, taxation and the extent of competition may vary. A graphic illustration is given by the diverging paths in SA goods and services prices sub-components, illustrated in relative price terms in Figures 1 and 2.

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 (Grunfeld and 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 (Hendry and Hubrich, 2006). Thus, well specified models in sample do 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 mainly focus on inflation rates rather than price levels, 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 rarely treated.

The focus on inflation rates rather than price levels 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.

In this paper, the first of its kind for an emerging market country, we investigate if there are gains to inflation forecast accuracy in SA by exploiting sectoral information and aggregating weighted forecasts of the sub-component price indices. We employ a more general approach than in earlier work for other countries, in richly-specified equilibrium correction models. SA's adoption of inflation targeting in 2000 aimed to enhance policy transparency, accountability and predictability, and has seen several improvements with evolving institutional design since 2000 (Aron and Muellbauer, 2009; Van der Merwe, 2004). The inflation target aimed to achieve a rate of increase in the overall consumer price index[2], excluding the mortgage interest cost (the so-called CPIX), of between 3 and 6 percent per year. Similar to the UK's original targeted index, RPIX, the mortgage interest cost is excluded, measuring mortgage-related housing costs in the CPI. Otherwise, raising interest rates to counter inflationary pressures also raises the interest cost component of measured inflation, and could provoke a further tightening of monetary policy.

Four-quarter-ahead forecasting models for the ten main sub-components of CPIX in SA are developed, combining equilibrium correction, trade openness and split trends to handle various structural shifts. These models permit the adjustment of prices to trends in relative prices and in prices relative to input costs to be part of the inflation process. We apply plausible restrictions to overcome the 'curse of dimensionality' in order to select parsimonious models. The sectoral four-quarter-ahead forecasts from the sub-component equations are aggregated using actual sub-component weights from the CPIX basket. The 'indirect' forecast thus obtained is then compared with various forecasts of the aggregate CPIX index. An improved understanding of inflationary pressures for particular sub-components of the basket of consumer spending could help to target micro-economic policy interventions, perhaps involving deregulation or the competition authorities.

2. Literature survey of disaggregated inflation forecasting studies

An analytical summary of known disaggregation studies of inflation is given in Table 1. The small, recent empirical literature largely emanates from central banks and addresses whether the accuracy of forecasts of aggregate inflation can be improved by disaggregation. The majority of studies apply to the Euro Area or its constituent countries, 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. A rather mixed view on the effectiveness of the method is presented by these studies. Table 1 notes the wide-spread omission of long-run equilibrium relationships and the exclusion of many theoretically-relevant determinants of inflation, including relative prices. The majority of studies estimate only in differences in log prices. Differencing can help avoid the forecast failure from structural breaks, a common source of forecast failure (Hendry and Clements, 2003), but the feedback relationships that help tie down sectoral price behaviour in the medium-run are missing.

One study on US data 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 it is supported for forecasting US inflation, in particular for a longer sample period from 1980 to 2004.

Turning to the Euro Area studies, a careful study by Hubrich (2005) explores differing selection procedures, but given the short samples, is constrained to differenced VARs and univariate models. She finds the indirect method, where the forecast of the aggregate is constructed from the weighted combination of the disaggregate forecasts, inferior to forecasting aggregate Euro Area year-on-year inflation directly for horizons of 12 months; but that for 'core' inflation (*HICPX*), when excluding difficult-to-forecast components such as energy and unprocessed food prices, the indirect method works better. This suggests there are gains to be made by better forecasting of some sectoral inflation rates. This conclusion was also reached by Fritzer et al. (2002), in a study on Austria, who suggests including better sectoral determinants. They find the disaggregated approach improves forecasting accuracy for *HICP* substantially for differenced ARIMA models; while in VAR models in levels (with a trend) it is superior for 10 to 12 months ahead. 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 employs 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 *HICP*s 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 cases there are improvements for the indirect approach, using disaggregated price information.

3. Price aggregates and trends in relative price components

The headline CPI for SA is a chained Laspèyres index with weights derived from consumer expenditure surveys in 2000, 1995, 1990, 1985 and earlier.[3] CPIX is defined as overall CPI excluding interest rates on mortgage bonds (the mortgage cost component of homebuyer's cost of housing). The relative price ratios, p_i/CPIX, of the 10 main components, i, of the CPIX since 1970, are shown in Figure 1 for goods and Figure 2 for services. The ten components comprise goods components (food (FD), furniture and equipment (FR), clothing and footwear (CL), vehicles (VH), transport goods (TG), beverages and tobacco (BT), and other goods (OG)); and services components housing (HX), transport services (TS), and other services (OS)). The construction of CPIX and of HX (the housing component that excludes the mortgage interest rate component) is discussed below in section 5.1. The construction of CPIX and HX is non-trivial and involves the use of 'level factors' (Aron and Muellbauer, 2004). We refer below to the weights for the CPI "metropolitan and urban" areas for the base year 2000: weights for the key categories are shown in Table 2.

Beginning with the goods components, the highest weighted and most volatile component is *food*, with a weight of 27.0 in the total CPIX index[4] for metropolitan and urban areas for the base year 2000. Food prices have tended to increase faster than the overall consumer price index since 1970, though between 1995 and 2001 the relative price was stable. The sharp increases in the early 1980s and early 1990s can be associated with drought conditions, as can rises after late 2001, which were exacerbated by a sharply depreciating currency. The weight of *furniture and equipment* in the total CPIX index is 3.1 percent, and that of *clothing and footwear* is 4.0 percent. The strong declining trend in the relative price of the furniture and clothing components in Figure 1, sharper from 1990, is likely to reflect more rapid productivity growth in this sector, as well as the opening of the economy to competing imports, which reduced the pricing power of producers in these sectors.

The weight of *vehicles* in the total CPIX index is 5.7 percent (new and used vehicles). The relative price ratio increased strongly over 1985-95, mainly due to a weak currency after 1984 increasing the cost of imported vehicles and imported vehicle components. Relative prices steadied around 1993; and from 1995, the relative prices of vehicles declined before stabilising from about 2000. Trade policy has also significantly influenced vehicles prices especially from 1995. The weight of *transport goods* in the total CPIX index is 5.8 percent, and this component encompasses both fuel and running costs. The fairly volatile relative price ratio is probably linked with frequent changes in motor fuel prices responding to world crude oil prices, and the impact of changes in the exchange rate.

The weight of *beverages and tobacco* is 3.0 percent. The sharp upward movement in the relative price index since 1994 is due to the high annual increases in excise duties on alcoholic and tobacco products, which far outpaced inflation. Finally, *other goods*, a miscellaneous category including prices for a wide variety of products[5], has a weight of 17.6 percent. The relative prices show a strong upward movement, especially from 1985 onwards, attributable to the sharp depreciation of the currency impacting on products with high import content. The effect of a more open economy is apparent from the early 1990s, with gradually falling relative prices.

Turning to the services components, the largest is *housing* with a weight in the total CPIX index for metropolitan and urban areas for the base year 2000 of 13.4 percent. Figure 2 shows the ratio to CPIX of housing excluding mortgage interest costs. House prices and mortgage costs feed gradually into rents, so that the rise in the relative price of HX in the early 1980s and after 1995 reflects the house price boom of the times, sometimes followed by a rise in interest rates, as in the 1984-5 debt crisis and in 1998. The relative price ratio of HX shows an extended decline from 1985 to 1995 as real house prices fell continuously, catalysed by falling interest rates from 1985 to 1987.

The two remaining services components are *transport services*, with a weight in the same total CPIX index in 2000 of 3.9 percent, and *other services* with a weight of 16.5 percent. The relative price of "transport services" declined from 1985 to 1989, paradoxically just when the relative price of vehicles rose most rapidly. The average annual inflation rate for transport services was less than 3 percent per annum after 1997. The other services category includes prices of a wide variety of products.[6] These have increased considerably faster than the total CPI index, especially from 1990 onwards. The main components include educational costs, the cost of medical services and other services, which encompass banking costs. The cost of education alone increased by 58.6 percent in 1993, compared to an average inflation rate of 9.7 percent; and from 1979 to 2003, increased by almost 6 percentage points per annum relative to CPI. The annual average increase in the price of the other services component was almost 3 percentage points higher than the total inflation rate after 1990.

4. Methodology

The dependent variable is the four-period-ahead rate of inflation, in single equation equilibrium correction models. The multi-step forecasting single equation models developed here have the advantage of simplicity over a full (VAR), see Sims (1980, 1996) on the rationale for using VARs. There are difficulties in interpreting and using VARs for policy and forecasting, arising from omitted variables (a restriction in another form), omitted structural breaks and relevant lags, and the use of sometimes doubtful identifying restrictions to give economic interpretations to shocks. 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. Recent research suggests that where VAR models suffer from specification errors such as omitted moving average error components or certain kinds of structural breaks – both important in South Africa - single-equation, multi-step models can provide more robust forecasts (Weiss, 1991; Clements and Hendry, 1996, 1998).

We propose a model of the following general type, for forecasting 4-quarter-ahead inflation rates for each of the ten components, p_i, of the CPIX, p :

$$
\begin{aligned}
\Delta_4 \log p_{i,t+4} = \alpha_i + \delta_i(\log p_t - \log p_{i,t}) + \sum_{j=0}^{k} \delta_{i,j} \Delta \log p_{t-j} \\
+\eta_i(\log wpi_{i,t} - \log p_{i,t}) + \sum_{j=0}^{k} \eta_{i,j} \Delta \log wpi_{i,t-j} \\
+\theta_i(\log ulc_t - \log p_{i,t}) + \sum_{j=0}^{k} \theta_{i,j} \Delta \log ulc_{t-j} \\
+\lambda_i(\log imp_t - \log p_{i,t}) + \sum_{j=0}^{k} \lambda_{i,j} \Delta \log imp_{t-j} \\
+\varphi_i(\log otherp_t - \log p_{i,t}) + \sum_{j=0}^{k} \varphi_{i,j} \Delta \log otherp_{t-j} \\
+\sum_{l=1}^{n} \beta_{i,l} X_{l,t} + \sum_{l=1}^{n} \sum_{j=0}^{k} \beta_{i,l,j} \Delta X_{l,t-j} \\
+\sum_{j=0}^{k} \omega_i \Delta \log p_{i,t-j} + \mu_{i,t} + \varepsilon_{i,t}
\end{aligned}
\qquad (3)
$$

where ε_{it} is white noise plus, possibly, a moving average error component, and μ_{it} is a combination of split trends and trade openness, reflecting institutional changes. The first five lines capture both the relative price "equilibrium correction" term and the dynamics for five types of prices: (i) total CPIX, so that if the i^{th} component of the CPIX index rises relatively, there could be some pressure to revert to the CPIX trend; (ii) wholesale price index component/s that might influence the corresponding CPIX component; (iii) unit labour costs; (iv) foreign prices such as import prices or world commodity price indices; and (v) *other* prices relevant to some components, such food prices, house prices, or an international oil price converted into domestic currency. Other potential long-run determinants are collected as the X_l variables on the penultimate line. These include, with sign priors in parenthesis, the terms of trade (+?), where a terms of trade boom drives up non-traded prices and also manufactured prices, depending on the extent to which they are shielded from world prices[7]; the real exchange rate[8] (-) measuring international competitive pressure on domestic price setters; the output gap (+) - either an economy-wide or a sector-specific output gap effect - since with higher excess demand, consumer prices may increase relative to wage costs and wholesale prices; the current account surplus (-), partly as an excess demand indicator, and partly as a predictor of exchange rate movements. In the current research, indirect taxation is ignored except in so far as it is captured by split trends[9] We also omit any direct effects of interest rates from the inflation forecasting models, given the conflicting interpretations of interest rate effects, and shifts in monetary policy regimes.[10]

Institutional changes are also likely to be important, for instance, changing trade policy may reduce inflation in some goods through increased import competition[11]. SA has experienced serious structural breaks in recent years. Generally, the impact of institutional changes or structural breaks is difficult to model.[12] Aron et al. (2009) explore potential structural breaks by modelling the price index components using, for 1979-2002, smooth non-linear stochastic trends to help indicate such shifts. These were estimated via the Kalman filter, in the STAMP package (Koopman et al., 2000). The shapes of these stochastic trends helped to date the two split trends used in this paper. The split trends are defined starting respectively in 1985q4 and 1995q1, and an eight-quarter moving average is taken to smooth their introduction. The first coincides with the September, 1985 debt crisis and the imposition of financial sanctions on SA in its aftermath; the second coincides with the opening up to capital flows in March 1995 (Aron and Muellbauer, 2009). The STAMP software is not suited for forecasting. We here use the Autometrics software (Doornik, 2009) to produce parsimonious models from a general specification in equation (3), partly to have an objective research tool. The results are reproducible using the same data, the same specification of the 'general unrestricted model' (GUM) and the same settings in Autometrics.

We have not applied the cointegration analysis of Johansen (1988), see Johansen and Juselius (1990). One major reason is the ubiquitous nature of structural breaks in SA. A second reason is that, in a quarterly context, the analysis applies to one-quarter-ahead models. One should not necessarily expect cointegration vectors relevant for one-quarter-ahead forecasts to remain relevant in a reduced form four-quarter-ahead forecasting model.

We are able to test for long lags without loss of parsimony by restricting the nature of longer lags. In most VARs, lag lengths are restricted to one or two quarters and rarely beyond four. The longer the lag, the more diffuse one would expect the effects to be since individual and sectoral heterogeneity is likely to spread the aggregate impact of shocks. This supports the case for allowing the possibility of longer lags, but restricting the effects to $\Delta_4 X_{t-4}$ and $\Delta_4 X_{t-8}$ or 4-quarter moving averages at such lags. For a variable such as the terms of trade, subject to erratic movements, annual or biannual changes or moving averages tend to smooth out erratic jumps in the data.

5. Results

Estimation and inflation forecasting results are presented in this section, and underlying data issues are discussed. The variables are defined in Table 3, where statistics are given and stationarity tests reported for the estimation plus forecasting sample, 1979q2-2007q4. The choice of sample was dictated by the period when the exchange rate floated (in one form or another), from the second quarter of 1979 onwards (Aron and Muellbauer, 2009).

The augmented Dickey-Fuller test statistics are based on specifications including a linear trend where this is significant, and lag lengths are based on the longest significant lag. The tests suggest that each log $p_{i,t}$ is I(1), implying that $\Delta_4$log $p_{i,t}$ is a stationary variable. The test statistics for the log level of the "other services" and "furniture" price components and of unit labour costs 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). The housing (HX) and food components and CPIX itself, are borderline without the trend, but the same point applies, with an implausibly low speed of adjustment. The statistics for the US maize price in rands and "transport goods" prices, however, suggest these log level prices are I(0). All other long-run explanatory variables are I(1), as expected, except for the output gap, the current account deficit and interest rate spreads, which are I(0).

Figures 3, 4 and 5 show the aggregate CPIX price index and the ten sub-component indices in log levels, first differences and annual changes, respectively. The log levels show smooth upward trends for the aggregate and all sub-indices with the exception of more traded goods categories, CL, FR and VH, which experienced price competition with the opening of the economy and reduced protection from 1990 onwards (definitions in Table 3). To some degree this is evident too in the OG category. The annual inflation rates exhibit downward trends for these four categories, and for the aggregate CPIX. Inflation has fallen for service categories, TS and OS. Inflation patterns are more erratic for the FD and HX components.

5.1 Data

The monthly CPI data and ten sub-components are available from 1997 for "metropolitan and urban" households, and it is on this survey that the targeted CPIX measure is based. We use the available sub-component CPI data for "metropolitan and urban" households, and splice it to the earlier CPI "metropolitan" components in January, 1997. All the above components are seasonally-adjusted from the South African Reserve Bank. The overall CPIX had to be constructed back to 1979q2 from seasonally unadjusted CPI "metropolitan" data following the method in Aron and Muellbauer (2004), and then spliced in 2000 (when CPIX became policy-relevant) to *Statistics South Africa's* seasonally unadjusted CPIX. We then seasonally adjusted this spliced CPIX series. We constructed HX, the housing component less the mortgage interest cost, back to the start of the sample for both the metropolitan component before 1997 and the "metropolitan and urban" component from 1997, using similar methods and appropriate weights (Table 2), and splicing the two in January, 1997. The unavoidable assumption to create historical data for the CPIX and its sub-components is that the price movements at the sub-component level do not differ greatly between the two types of survey.

For unit labour costs in manufacturing we use a measure adjusted for variations in capacity utilisation. Log unit labour costs are defined as log earnings per head minus log output per head. Log output per head (labour productivity) varies with short term capacity utilisation. To adjust for this effect and to get closer to underlying movements, we regress log output per head, log (PROD), on a smooth stochastic trend (STOCHTR) and current and lagged effects of a capacity utilisation measure (log (CAPUT)) using STAMP. This gives log (PROD) = f(log(CAPUT)) + STOCHTR + ε. We then take (log (PROD) - f(log(CAPUT))), where the parameters of f() are estimated for 1976 to 2002 as an estimate of the trend in cyclically adjusted labour productivity.[13]

Changing openness to international trade has been important in SA especially since 1990 (Edwards et al., 2009). Lower foreign trade taxes are consistent with lower producer prices from cheaper imported inputs, and this tends to lower consumer prices. With lower import tariffs, domestic producers face greater potential competition, further discouraging price rises. The measure of trade openness we use in this paper is defined by a four-quarter moving average of exports plus imports relative to GDP, all measured in constant prices. This is used in most of the forecasting models.

5.2 Forecasting results

In this section, the results of forecasting exercises are presented from naïve and sophisticated models. The dependent variables are the one-year ahead annual changes for all ten CPIX sub-component prices, and for the aggregate CPIX itself. The sample is split into an estimation period and a forecast evaluation period. Model selection and estimation is carried out over 1979q2 to 2002q2, and then recursive forecasts are generated adding a quarter at a time, up to 2007q4.[14]

The root mean square forecast errors (RMSFE) for each model and each dependent variable is given in Table 4. The penultimate column shows RMSFEs for the 'direct' forecast, that of the aggregate CPIX. The final column presents RMSFEs for the 'indirect' forecasts, that is, where the sectoral h-step forecasts from the sub-component equations are aggregated using actual sub-component weights from the CPIX basket. Comparison of the RMSFEs for the final two columns thus shows the gains in forecasting from sectoral models.

The structure of the six naïve models each using different information sets is given below the table. The first five models are univariate autregressive models, using only differenced lagged own price information. These are regressions on a constant capturing a random walk with drift in the log price level (*Model 1*); on the current annual inflation rate (*Model 2*); on an AR(4) in quarterly inflation rates and the annual inflation rate lagged four quarters (*Model 3*); on a slightly more parsimonious version of *Model 3* using the current quarterly inflation rate, the two quarter inflation rate and its two-quarter lag, and the four quarter inflation rate lagged four quarters (*Model 4*); and on an AR(9) in quarterly inflation (*Model 5*). The sixth naïve model, *Model 6*, is *Model 3* augmented with an openness indicator, DOPEN, lagged changes in the output gap and in the current account balance to GDP.

We then extend the information set in two 'general unrestricted models' (GUMs), based on the framework in Section 4. These are used to generate parsimonious models with automatic model selection using Autometrics, Doornik (2009).[15] In our context, the overlapping nature of the dependent variable means that residuals will be auto-correlated and so we switch off the corresponding tests, including portmanteau tests. We use heteroscedasticity and autocorrelation corrected (HAC) t-ratios and F-tests for model selection; we have not used the outlier option, though potentially this could be helpful for detecting institutional one-off events that could be addressed with dummies e.g. droughts. Model selection given a GUM involves two potential errors: omitting relevant variables and including irrelevant variables. Heavy protection against the latter can result in smaller models being chosen. We choose the default setting, limiting the probability to 0.05 of including an irrelevant variable, see Doornik (2009) for further details.

The structure of the two GUMs is given beneath Table 4. *GUM1* has no long-run terms, but it has a rich dynamic specification in a range of prices compared to the naïve models. *GUM1* augments *Model 6* with the wholesale price index, import price, oil price in rand terms, the aggregate CPIX, unit labour costs, the real effective exchange rate and terms of trade, using the same specification of lags in changes to logs. The openness indicator, DOPEN, is included in every equation. *GUM2* is based on *GUM1*, but it also includes long-run information: equilibrium correction terms in all the above prices, plus levels in the output gap and the ratio of the current account surplus to GDP.

Where possible, additional *sectoral* equilibrium correction terms were included in *GUM2* for different sub-components, which were based on disaggregation of wholesale price data. For the CPI components: "clothing", "beverages and tobacco", "furniture" and (processed) "food", there are direct matches from the disaggregated wholesale price index (WPI) data, and the component WPI to component CPI ratios could be included. We include an additional relative price between CPI food and "raw" food, an unpublished sub-component of the wholesale price component for "Agriculture, forestry and fishing". The "other goods" CPI component includes miscellaneous manufactured goods (see section 4) and we thus included a relative price with the manufactured goods wholesale price component. For CPI “vehicles” and “transport goods” components, the relative prices to the wholesale price “metals and machinery” sub-component were tested for. For the CPI “housing” component, the relative price to the “medium-sized houses” price was included in *GUM2*. The openness indicator, DOPEN, is also included in every equation.

For all 11 equations in *GUM2*, two split trends were included. These are respectively zero before 1985Q4 and 1995Q1 and then increase linearly with time. The eight-quarter moving average is taken to smooth the impact of structural shifts, and advanced four quarters, given the four-quarter-ahead inflation rates being modelled. As mentioned above, these datings, in 1985 and 1995, mark watersheds in post-war SA history. The stochastic trends used in Aron et al. (2009) tend to show particularly large shifts in slope around these dates.

The equations selected by Autometrics are summarised for *GUM1* and *GUM2* in Appendix 1.[16] The following *a priori* restrictions were imposed for models containing equilibrium correction terms and other long-run terms, consistent with the discussion in Section 4. Positive coefficients are expected on all equilibrium correction terms and on the output gap, and negative coefficients on the log real exchange rate and the ratio of the current account surplus to GDP. No signs are imposed on the log terms of trade, given the sign ambiguities and dynamic terms were also left intact. The DOPEN term is expected to have a negative sign for traded goods, but could have a positive effect for non-traded services; the negative sign restriction was only imposed for the former. Sign restrictions were imposed as follows: if the initial model selected from the GUM failed one or more sign restrictions, the term with the most statistically significant of the failures was eliminated from the GUM and a new model selected from the revised GUM. This procedure was repeated until sign violations were eliminated.

To summarise Table 4, the general points that emerge are as follows. First, there is a clear gain from using multivariate sectoral information in forecasting. In the naïve models based only on CPIX price data, the weighted ‘indirect’ forecast does not improve on the ‘direct’ forecast for aggregate CPIX inflation. However, in *GUM1*, incorporating other information such as changes in the wholesale price index, the real exchange rate etc., but without equilibrium correction, the weighted ‘indirect’ forecast is significantly superior to naïve model ‘direct’ forecasts from Models 1 to 6, and also superior to the ‘direct’ forecasts of CPIX using *GUM1*. The models with equilibrium correction (i.e. *GUM2*) give further gains in forecast performance relative to naïve bench-marks, and the weighted ‘indirect’ forecast also outperforms the ‘direct’ forecast using *GUM2*.

Second, in the aggregate equation alone (i.e. the ‘direct’ forecast in the penultimate column), there is a substantial gain in forecast accuracy from using the more sophisticated *GUM*1 equations relative to simpler naïve models, and a further gain from using *GUM2* with its error correction terms. For instance, the shift from the better naïve models, *Model 4* and *Model 5,* to *GUM1* with a richer specification but no error correction terms, achieves a 28 percent reduction, from 0.0260 to 0.0187, in root mean squared forecast error. The shift to *GUM2* achieves a 33 percent reduction in root mean squared forecast error, from 0.0260 to 0.0175.

Third, in the sub-component equations, the RMSFEs from using the more sophisticated *GUM2* equations generally improve relative to the naïve models and *GUM1*. The exceptions are for sub-components where there has been substantial structural change, perhaps imperfectly picked up by the split trends (e.g. a shift in the house price to rent relationship for housing, and large changes in taxation for beverages and tobacco, BT, and vehicles, VH). There the error correction version, *GUM2*, performs less well than the better naïve models. With “other goods”, OG, spanning a hugely diverse range of products, a similar result is found.

Fourth, it proves important to take account of institutional and structural change. The split trends are highly relevant in all sectoral equations, though not in the overall CPIX equation. Increasing trade openness has substantially reduced the inflation rate in SA, reducing relative prices and inflation rates of the more tradable goods and of those goods where the pressure of international competition has contributed to higher productivity growth (e.g. furniture, clothing, vehicles and other, largely manufactured, goods). Conversely, the relative prices of goods and services more sheltered from these international competitive pressures, e.g. housing, HX, have tended to rise.

Finally, model selection appears to have slightly greater benefits at the aggregate level than for the sub-component equations. The *GUM2* specification was used to forecast *without* employing Autometrics for reducing general to parsimonious models (detailed results are not reported). However, sign priors were imposed, by sequentially eliminating terms violating these priors, as above.

For individual CPI component equations, the forecasting results are mixed: RMSFEs improve for about half and deteriorate for the other half relative to the reported *GUM2* results which use model selection. For the weighted indirect forecasts, the RMSFE improves by around 0.005 by not using automatic model selection. For the single equation direct forecasts, the RMSFE worsens by around 0.005 when automatic model selection is not used, widening the gap between the indirect and the direct forecasting performance, compared to the results reported in Table 4. However, the test posed in this paper for the automatic selection method is tougher than real time forecasters actually face. Model selection takes place just once – for the 1979q2 to 2002q2 sample. In practice, real time forecasters could reselect the parsimonious model on a rolling quarterly basis, allowing the model to react better to structural breaks and other new information on the parameters.

5.3 The specifics of the aggregate CPI index equation

We turn to the specifics of the more richly specified *GUM2* equation for aggregate CPIX. At the aggregate CPIX level, the findings make good economic sense. In Figure 6, the long-run variables relevant in the aggregate CPIX equation of *GUM2* are shown: DOPEN, the log real exchange rate, the log terms of trade, the output gap and the relative price ECM terms in rand oil prices and unit labour costs. There are strongly significant equilibrium correction terms with respect to unit labour costs and to oil prices, both with long lags.[17] The log real exchange rate brings in strong effects from foreign prices and the exchange rate. Increased trade openness is shown to have been important in reducing inflation in SA. The terms of trade and the output gap have inflationary effects, again with long lags.

To indicate the type of results obtained, the estimated aggregate equations for CPIX are reported in Appendix 2 for both *GUM1* and *GUM2*, but run over the whole sample. The fit is only marginally worse than for the estimated sample up to 2002q2, and the model is robust to testing for outliers.

The specifics of the corresponding sectoral equations are presented in Appendix 3 to gain insight into the underlying influences on aggregate and sectoral inflation in SA (*GUM2* specifications for the sectoral equations are given in Appendix 1).

6. Conclusion

This study, the first of its kind for an emerging market country, has investigated gains to inflation forecast accuracy by aggregating weighted forecasts of the sub-component price indices, versus forecasting the aggregate consumer price index itself. Using more richly specified equilibrium correction models than hitherto in the literature, we have modelled separately the inflation rates for the ten major groups of goods and services that make up the consumer price index excluding the mortgage cost component, i.e. CPIX. This involved some data construction to extend the sample back since published CPIX data go back only to 1997. The models have been designed to explain the separate inflation rates four quarters ahead, bringing to bear relevant economic and institutional knowledge. As well as serving as a prelude to designing practical forecasting models for overall inflation, these models cast important light on the complex forces acting on the relative prices and inflation rates of the different goods and services, explaining higher inflation rates in some sectors and the different persistence of shocks in the different sectors. Our models have reasonable economic interpretations at both the aggregate and sectoral levels.

We selected models for 1979-2002 and recursively forecast to the end of 2007, to compare the performance of models corresponding to differing information sets. For one-year-ahead inflation forecasting, using naïve models based only on CPIX inflation data, the weighted 'indirect' forecasts do not improve on the corresponding naïve 'direct' forecast for aggregate CPIX inflation, see Table 4. Then more comprehensive information sets were examined. Our methods have three main ingredients: design of the GUM (general unrestricted model), including permitting longer lags than conventionally considered but without suffering the 'curse of dimensionality'; the use of Autometrics to select parsimonious models from each GUM; and the use of sign priors on the long-run responses to shocks. Applying these methods to an aggregate CPIX equation incorporating changes in the wholesale price index, unit labour costs, the real exchange rate, import prices, terms of trade, oil prices, the output gap and trade balance to GDP ratio, and the level of trade openness achieves a 28 percent reduction, from 0.0260 to 0.0187, in root mean squared forecast error relative to the better naïve models for aggregate CPIX. These naïve models use lags up to eight quarters in lagged aggregate inflation. The selected aggregate CPIX forecasting equation contains strongly significant lags up to eight quarters, outside the range conventionally considered in VAR-based forecasting models. Applying the same methods to each of the inflation components, and weighting the forecasts using the CPIX weight to obtain an 'indirect' forecast for CPIX, brings a further reduction in the RMSFE from 0.0187 to 0.0177, resulting in a 32 percent gain relative to the naïve model benchmark..

In a further extension of the data to bring in equilibrium correction terms in relative prices, and the levels of the output gap, trade balance, terms of trade, the real exchange rate, and split trends, forecasts from the aggregate CPIX equation have an RMSFE of 0.0175, 32.5 percent lower than the better naïve models. Applying these extensions to the data set for the individual CPIX components, and in addition, bringing in specific sectoral information such as house prices in the housing cost equation and the wholesale price index for food manufacturing in the food equation, we obtain a total reduction of 41 percent in RMSFE to 0.0154 relative to the naïve benchmark of 0.0260.

At the aggregate CPIX level, we find long lags in strongly significant equilibrium correction terms with respect to unit labour costs and to oil prices, and also in the terms of trade and the output gap. Indeed, we find more generally that far longer lags are relevant than conventionally considered in VAR modelling. The standard technique in VAR studies of using an information criterion to select the optimum lag implies short lags, which typically results in models which forecast less well.[18] The relevance of longer lags has been brought to light by our technique of using parsimonious representations of longer lags to overcome the 'curse of dimensionality'. Instead of taking nine parameters to represent a maximum lag of nine quarters, we use four. This saving makes it possible to consider a richer menu of driving variables than conventionally used in VAR studies. The further parsimony from use of automatic model selection helps to overcome an important source of forecast error, namely parameter estimation uncertainty, which is an aspect of the 'curse of dimensionality'.

It is interesting that the most dramatic gains relative to the naïve model come from extending the data set for an aggregate CPIX equation, and using our GUM design and automatic model selection strategies to find more parsimonious forecasting equations. However, it is gratifying that further gains are available from modelling at the sub-component level since there is considerable potential for further improvements in model specification at this level. For example, explicit treatment of tax policy and regulatory information, for example concerning the car industry, is likely to improve some of these equations considerably. Furthermore, in practical real time forecasting, there is often information on announced planned price rises, for example for electricity prices, going forward a year or more. Combining this kind of information with forecasts from the models should make it possible to improve further on these forecasting methods.

We have concentrated on forecasting four quarters ahead. But exactly the same exercise could be carried out at shorter and less challenging horizons one and two quarters ahead. Further extensions to this work are possible. The sectoral equations could be tested for the relevance of outliers, indicating the possible application of dummies reflecting known institutional changes corresponding to the identified outliers. The potential relevance of interest rates and spreads could also be tested for, though we have above indicated likely difficulties in terms of ambiguous signs, and the effects from structural breaks in monetary policy (e.g. a period during 1985-1993, when interest rate policy was directed at maintaining current account surpluses to help fund the required outflows for debt repayments). Non-linearities could be tested for, such as asymmetric effects from oil price changes; and also exploring the changes in coefficients with structural change, such as changing openness.

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Table 1: Typology of known disaggregation studies of inflation.

Study	Area	Price	Frequency	Model methodology	Long-run terms and relative prices?	Components
Moser, Rumler & Scharler (2007)	Austria	HICP	Monthly	Factor models, VAR and ARIMA models, and combining forecasts from factor and VAR models (VAR variables for 5 models, selected are interest rates, bank deposits, producer prices, M3, exports, unemployment, wages, manufacturing orders, industrial production)	All ARIMA and VAR models are estimated in first *differences*	5 main components of the HICP
den Reijer & Vlaar (2006)	Netherlands; Euro area	HICP	Monthly estimation 1987:10-1990:1	VAR in first differences for unprocessed food, energy and for Euro Zone processed food, and VECM in both first and 12-month differences for the other indices, with equilibrium relationships between HICP components and other variables, notably the hourly wage rate and import or producer prices.	The long-run error-correction terms in annual inflation rates – i.e. *differences* only.	5 main components of the HICP
Hendry & Hubrich (2006)	Euro Area, USA	HICP, CPI (USA)	Monthly Euro: 1992:1-2001:12 or 2004:12 USA: 1990-2004, 1980- 2004	Different selection procedures are used for a range of models (see p19): autoregressive (AR) models, vector autoregressive model for subcomponents, vector autoregressive model for aggregate and sub-components, factor models	*Differenced* models *[Note difference to other studies*: sub-components are added on RHS of the aggregate model]	5 components of HICP: processed food, unprocessed food, energy, industrial goods and services; 4 components of USA CPI: food, industrial goods, services & energy
Hubrich (2005)	Euro Area	HICP	Monthly estimation 1992:1-1998:1 forecasting 1992:1-2001:12	Univariate (random walk and AR) and VAR models including broader data set (industrial production, M3, producer prices, import prices, unemployment, unit labour costs, commodity prices (excl. energy) in euro, oil prices in euro, nominal effective exchange rate, short-term and long-term nominal interest rate), various selection procedures	*Differenced* models only	5 main components of the HICP
Albacete & Espasa (2005)	Euro Area	HICP	Quarterly estimation 1993q3-99q4 monthly	Combine monthly time series vector model on HICP sub-indexes in differences, and quarterly vector model on HICP and other economic variables (import deflator, ULC, output gap GDP, unemployment, M3) in differences but with cointegrating terms	Long-run cointegrating relations between the aggregate index and other variables in *levels*	Disaggregate HICP by countries and sectors.
Espasa & Albacete (2007)	Euro Area	HICP	Monthly Total sample	ARIMA models and vector error correction models (VECM) that impose cointegration relations between HICP sub-indices.	Long-run cointegrating relations between the sectoral prices of	5 countries & 2 sectors: overall index (excl. energy & unprocessed

Study	Area	Price	Frequency	Model methodology	Long-run terms and relative prices?	Components
			1996:1-2001:7		different countries in *levels*	food) & energy & unprocessed food.
Benalal, Landau, Roma & Skudelny (2004)	Euro area, & 4 largest countries	HICP	Monthly total sample 1990:1-2002:6	Univariate (random walk, ARIMA, exponential smoothing) and multivariate (VAR, Bayesian VAR, single equations) models, other variables tested include oil and non-oil commodity prices, nominal effective exchange rate, short-term interest rates, compensation per employee and real GDP growth, VAT, energy taxation, import prices and producer prices)	*Differenced* models only	5 main components of the HICP and 4 largest euro area countries.
Peach, Rich & Antoniades (2004)	USA	PC	Monthly	Single equation error correction models for differenced goods price inflation and services price inflation	Long-run cointegrating relation in *differences* only, i.e. between goods and services infl.	Goods & services component sub-totals
Fritzer, Moser & Scharler (2002)	Austria	HICP	Monthly estimation 1987-1996 forecasting 1996-2000	(12-step ahead) VAR and ARIMA models, using sector specific variables.	VAR models estimated in *levels* with a trend	Headline, unprocessed food, processed food, services and energy
Espasa, Poncela & Senra (2002)	USA	CPI	Monthly estimation 1983-1997 forecasting 1998-2000	Univariate ARIMA models, all models are in second differences. Multivariate forecasts (12-step ahead) from cointegration and dynamic factor models: not reported as they did not outperform the univariate forecasts	I(2) analysis: hence long-run terms in *differences* only	Food, non-energy commodities, services and energy.
Espasa, Senra & Albacete (2002)	Euro Area	HICP	Monthly total sample 1996-2001	ARIMA models and vector error correction models (VECM) that impose cointegration relations between HICP sub-indices.	Long-run cointegrating relations: between the sectoral prices of countries in *levels*	5 countries & 2 sectors: overall index (excl. energy & unprocessed food); & energy & unprocessed food.
Jondeau, Le Bihan & Franck Sédillot (1999)	French	CPI	Quarterly	Single equation error correction models (including subsets of variables: capacity utilisation import prices and unit labour costs, plus dummies)	Long-run term is in *differences* only	Food excl. “sensitive” products, manufactured goods, services (plus rents and water); other components exogenous

Table 2: Weights for the consumer price index

	Coverage	Metropolitan areas						Metropolitan and urban areas	
	Components	**Apr 70 - Dec 77**	**Jan 78 - Oct 87**	**Nov 87 – Jul 91**	**Aug 91 - Dec 96**	**Jan 97- Dec 01**	**Jan 02 -**	**Jan 97- Dec 01**	**Jan 02 -**
Services	Housing	21.6	19.5	22.5	20.5	26.0	24.3	24.3	22.3
	Mortgage interest cost	3.61	3.4	9.47	11.51	12.91	11.43	11.1	10.3
	Transport	4.9	3.7	5.9	4.3	4.3	3.4	3.6	3.5
	Other	7.1	9.7	11.1	17.3	14.7	15.2	14.7	14.8
	Total	33.6	32.9	39.5	42.1	45.0	42.9	427	40.6
Goods	Food	23.9	25.5	23.2	19.3	18.8	22.1	20.3	24.2
	Furniture and equipment	7.8	6.0	4.7	5.5	3.9	2.5	4.3	2.8
	Clothing and footwear	9.6	8.8	6.0	7.0	4.8	3.2	5.1	3.6
	Vehicles	6.7	5.6	5.5	5.5	5.3	6.0	5.3	5.1
	Transport goods	5.0	5.6	5.9	4.6	5.2	5.5	5.2	5.2
	Beverages and tobacco	4.1	3.8	2.3	2.2	2.1	2.5	2.2	2.7
	Other	9.3	11.8	12.9	13.8	14.9	15.3	14.9	15.8
	Total	66.4	67.1	60.5	57.9	55.0	57.1	57.3	59.4
Total CPI		100.0	100	100.0	100.0	100.0	100.0	100	100
Total CPIX							NA	88.9	89.7

Source: South African Reserve Bank and *Statistics South Africa.*
Notes: The composition of the deflators:
Vehicles: Includes personal transport equipment and motorcars tyres, parts and accessories.
Transport running costs: Includes household fuel and power and petroleum products.
Other goods: Includes recreational and entertainment goods, other durable goods, household textiles, furnishings and glassware, personal goods and writing and drawing equipment, household consumer goods, medical and pharmaceutical products.
Housing: Includes rent, incorporating rent for owner-occupied dwellings and
Transport: Includes transport and communication services household services.
Other services: medical services, recreational, entertainment and educational services and other miscellaneous services.

Table 3: Statistics and variable definitions.

Sub-component equations	Definition of variable	Mean	Std Dev.	I(1)[a]	I(2) [a]
log (CPIXC)	Log of CPIX, the consumer price index excluding mortgage interest costs – constructed as per section 5.1, then seasonally adjusted	3.84	0.889	-0.658	-3.81*
log (HX)	Log of the "housing" sub-component of CPI with the mortgage interest component subtracted – constructed, details in section 5.1	3.83	0.909	-0.300	-3.90*
log (TS)	Log of the "transport services" sub-component	4.11	0.623	-2.84	-3.56*
log (OS)	Log of the "other services" sub-component of CPI	3.70	1.02	1.48	-9.92**
log (FD)	Log of the "food" sub-component of CPI	3.83	0.941	-1.21	-5.25**
log (FR)	Log of the "furniture" sub-component of CPI	4.11	0.626	0.653	-4.90**
log (CL)	Log of the "clothing" sub-component of CPI	4.06	0.616	1.45	-4.60**
log (VH)	Log of the "vehicles" sub-component of CPI	3.76	0.994	-2.77	-3.65*
log (BT)	Log of the "beverages and tobacco" sub-component of CPI	3.64	1.081	-1.89	-5.06**
log (TG)	Log of the "transport goods" sub-component	3.90	0.793	-4.24**	-5.73**
log (OG)	Log of the "other goods" sub-component of CPI	3.85	0.877	-2.71	-3.90*
log (WPIMP)	Log of the wholesale price for imported goods	3.97	0.784	-3.33*	-5.68**
log (IMPD)	Log of import prices measured as: log of National Accounts total imports deflator.	-0.698	0.786	-2.40	-11.0**
log (WPDTOT)	Log of the wholesale price for total domestic goods	3.97	0.784	-1.278	-5.68**
log (WPMTOT)	Log of the wholesale price for manufactured goods	3.96	0.803	-3.310*	-5.06**
log (WPAG)	Log of the wholesale price for agriculture, forestry and fishing	4.09	0.687	-2.75	-4.33**
log (AGFOOD)	Log of the wholesale price for raw food from the above category	4.00	0.779	-1.54	-3.96**
log (WPFD)	Log of the wholesale price for food	4.12	0.678	-3.05	-5.25**
log (WPBT)	Log of the wholesale price for beverages and tobacco	3.87	0.879	-2.28	-6.21**
log (WPCL)	Log of the wholesale price for textiles, clothing and footwear	4.00	0.736	-2.29	-3.74*
log (WPMET)	Log of the wholesale price for basic metals and products	4.00	0.787	-1.266	-4.85**
log (WPMACH)	Log of the wholesale price for machinery and transport equipment	3.97	0.809	-3.16*	-4.66**
log (USMAIZER)	The rand price of US maize (Chicago)using the bilateral rand/$ exchange rate	5.86	0.724	-4.02*	-8.65**
log (ULC)	Log of manufacturing unit labour costs, adjusted to remove a productivity trend, see section 5.1	7.29	0.808	-0.434	-6.08**
log (POILR)	Log of (Rand) Brent oil price	4.39	0.875	-2.12	-9.01**
log (HPRICE)	Log of the house price, total SA: New & Old - Medium - Purchase Price - Smoothed (ABSA)	11.9	0.878	-2.40	-3.87**
log (NEER)	Log of the nominal effective exchange rate, spliced in 1990 and 1978 to previous series with different weights.	5.27	0.751	-1.35	-4.62**
log (REER)	Log of the real effective exchange rate, spliced as above.	4.74	0.144	-3.30	-4.79**
log (TOT)	Log terms-of-trade	4.71	0.0739	-3.30*	-15.0**
PRIME	Prime rate/100	0.162	0.0394	-3.38*	-6.18**
RPRIME	Prime rate/100 less the annual change in the log of CPIXC	0.0590	0.0484	-3.62**	-5.14**
SPRTBILL	Spread between the SA gov. 10 year bond rate/100 and the SA T bill rate/100.	0.0132	0.0283	-3.51**	-6.74**
SPRPRIME	Spread between the SA gov. 10 year bond rate/100	-0.0282	0.0274	-2.78	-6.49**

Sub-component equations	Definition of variable	Mean	Std Dev.	I(1)[a]	I(2)[a]
	and the PRIME/100.				
DOPEN	Conventional trade policy measure in real terms: ratio of real exports plus real imports to real GDP, 4-quarter moving average	33.3	8.85	2.535	-6.01**
DOPENC	Constructed trade policy measure, see text.	-	-	-	-
SPLIT854	Split trend beginning in 1985q4, 8-quarter moving average, lead by 4 quarters	-	-	-	-
SPLIT951	Split trend beginning in 1995q1, 8-quarter moving average, lead by 4 quarters	-	-	-	-
OUTGAP	The output gap measured as: log real GDP adjusted with a Hodrick Prescott filter (lambda=1600) for log potential GDP	0.000834	0.0162	-4.77**	-
RCURBAL	Current account surplus to GDP ratio, both seasonally adjusted	-0.00326	0.0377	-3.64**	-

Source: All variables from the *Quarterly Bulletin*, South African Reserve Bank, except house prices (ABSA), and the prime rate, US maize price and Brent oil price (from IFS, International Monetary Fund).
Notes:
1. The statistics are produced for the estimation plus forecasting sample, 1979q2-2007q4. Statistics are reported to three significant figures.
2. For a variable X, the augmented Dickey-Fuller (1981) statistic is the t ratio on π from the regression: $\Delta X_t = \pi X_{t-1} + \Sigma_{i=1,k} \theta_i \Delta X_{t-i} + \psi_0 + \psi_1 t + \varepsilon_t$, where k is the number of lags on the dependent variable, ψ_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 only if significant. For null order I(2), ΔX 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 i.e. before taking moving averages and changes.
3. For the following: log(HX), log(OS), log(FD), log(FR), log (ULC), log (WPMET), and log (WPDTOT), 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).
4. From January, 2009, the CPI weights changed with the rebasing of the CPI, and a new measure of housing costs based on imputed rents was introduced.

Table 4: Naïve models and GUMs: root mean square forecasting errors for the aggregate price index 4-quarter-ahead forecasts, the sub-indices price 4-quarter-ahead forecasts, and the aggregated weighted sub-indices (indirect) 4 quarter ahead forecasts, 2003q2-2007q4.

Dep. Variable (4-q ahead)	**$\Delta_4$log HX**	**$\Delta_4$log TS**	**$\Delta_4$log OS**	**$\Delta_4$log FD**	**$\Delta_4$log FR**	**$\Delta_4$log CL**	**$\Delta_4$log VH**	**$\Delta_4$log BT**	**$\Delta_4$log TG**	**$\Delta_4$log OG**	**$\Delta_4$log CPIX**	**IND**
	Housing Services excluding mortgage interest rate	*Transport Services*	*Other Services*	*Food*	*Furniture and equipment*	*Clothing and footwear*	*Vehicles*	*Beverages and tobacco*	*Transport goods*	*Other Goods*	*Total CPIX*	*Indirect aggregated sub-component Forecast*
Model 1	0.0535	0.0475	0.0686	0.0742	0.0812	0.1241	0.1207	0.0420	0.0780	0.0687	0.0613	0.0631
Model 2	0.0332	0.0261	0.0351	0.0629	0.0375	0.0598	0.0513	0.0339	0.0764	0.0300	0.0265	0.0356
Model 3	0.0336	0.0262	0.0318	0.0580	0.0343	0.0504	0.0390	0.0304	0.0847	0.0280	0.0259	0.0323
Model 4	0.0335	0.0259	0.0318	0.0581	0.0340	0.0504	0.0388	0.0303	0.0843	0.0285	0.0260	0.0324
Model 5	0.0347	0.0273	0.0319	0.0585	0.0341	0.0501	0.0392	0.0314	0.0835	0.0254	0.0260	0.0318
Model 6	0.0337	0.0246	0.0273	0.0485	0.0217	0.0535	0.0280	0.0222	0.0845	0.0243	0.0266	0.0283
GUM1	0.0469	0.0248	0.0233	0.0397	0.0299	0.0520	0.0181	0.0305	0.1025	0.0217	0.0187	0.0177
GUM2	0.0532	0.0218	0.0209	0.0233	0.0196	0.0498	0.0582	0.0320	0.0733	0.0373	0.0175	0.0154

Notes: Statistics are reported to three significant figures.

1. Weighting for IND uses 2002 weights for "metropolitan and urban" CPI out of 89.7, the total for CPIX (Table 2).

2. Naïve models for price component x (using definitions in Table 3):

MODEL 1: OLS $\Delta_4\log(x)_{t+4}$ constant [RW in prices with drift]

MODEL 2 OLS $\Delta_4\log x_{t+4}$ constant, $\Delta_4\log x_t$

MODEL 3: OLS $\Delta_4\log x_{t+4}$ constant, $\Delta\log x_t$, $\Delta\log x_{t-1}$, $\Delta\log x_{t-2}$, $\Delta\log x_{t-3}$,$\Delta_4\log x_{t-4}$

MODEL 4: OLS $\Delta_4\log x_{t+4}$ constant, $\Delta\log x_t$,$\Delta_2\log x_t$,$\Delta_2\log x_{t-2}$, $\Delta_4\log x_{t-4}$

MODEL 5: OLS $\Delta_4\log x_{t+4}$ constant, $\Delta\log x_t$, …, $\Delta\log x_{t-8}$

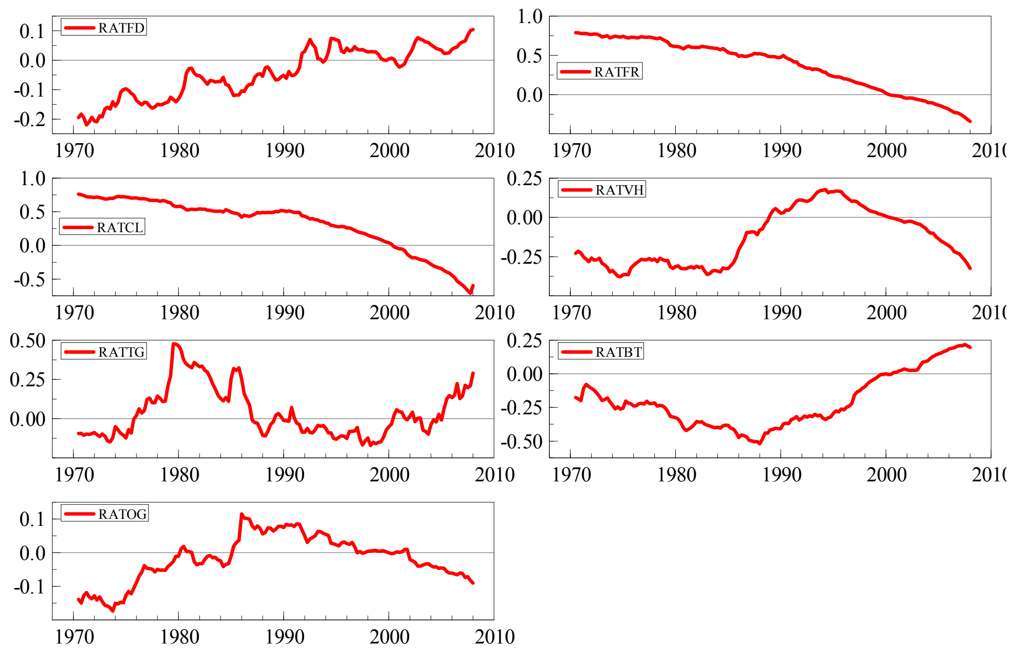
MODEL 6: OLS $\Delta_4\log x_{t+4}$ constant, $\Delta\log x_t$, $\Delta\log x_{t-1}$, $\Delta\log x_{t-2}$, $\Delta\log x_{t-3}$, $\Delta_4\log x_{t-4}$, DOPEN, $\Delta OUTGAP_t$-$\Delta OUTGAP_{t-4}$, $\Delta RCURBAL_t$-$\Delta RCURBAL_{t-4}$

3. GUMS for price component x (using definitions in Table 3):

GUM1: OLS $\Delta_4\log x_{t+4}$ constant, $\Delta\log x_t$, $\Delta_2\log x_t$, $\Delta_2\log x_{t-2}$, $\Delta_4\log x_{t-4}$, DOPEN, ΔZ_t , $\Delta_2 Z_t$, $\Delta_2 Z_{t-2}$, $\Delta_4 Z_{t-4}$
where $Z\in\{$ log WPIDTOT, log IMPD, log CPIXC, log ULC, log POILR, log REER, log TOT, OUTGAP, RCURBAL$\}$

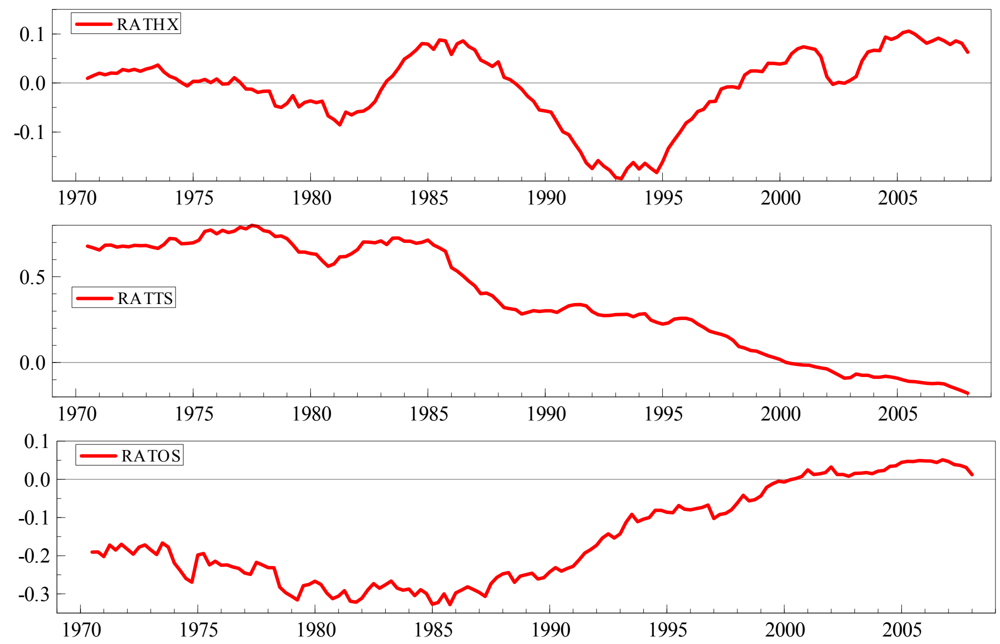
GUM2: OLS $\Delta_4\log x_{t+4}$ constant, $\Delta\log x_t$, $\Delta_2\log x_t$, $\Delta_2\log x_{t-2}$, $\Delta_4\log x_{t-4}$, DOPEN, ΔZ_t , $\Delta_2 Z_t$, $\Delta_2 Z_{t-2}$, $\Delta_4 Z_{t-4}$,
log $REER_t$, log TOT_t, $OUTGAP_t$, $RCURBAL_t$, SPLIT854, SPLIT951, $(\log ULC - \log x)_t$,
$(\log POILR - \log x)_t$, $(\log IMPD - \log x)_t$, $(\log CPIXC - \log x)_t$, $(\log WPIDTOT - \log x)_t$, $(\log OTHERP - \log x)_t$
where $Z\in\{$ log WPIDTOT, log IMPD, log CPIXC, log ULC, log POILR, log REER, log TOT, OUTGAP, RCURBAL$\}$

Figure 1: Relative prices of CPIX components to CPIX: goods



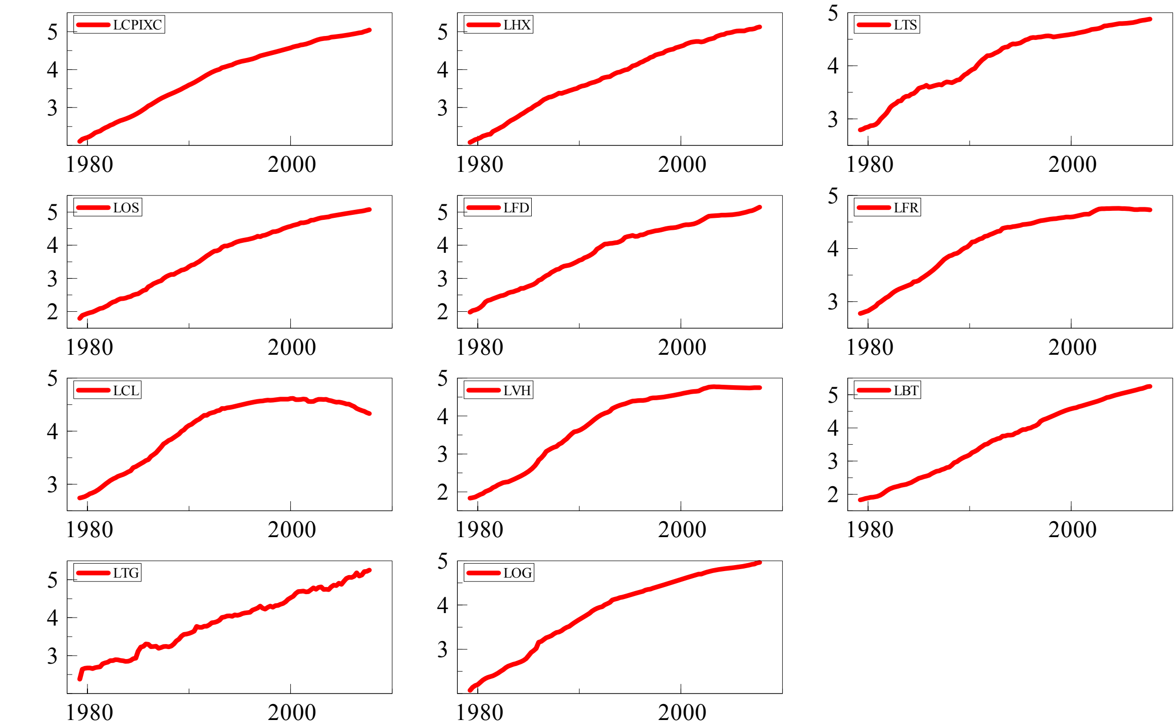
Notes: RAT refers to the ratio of the component to total CPIX, definitions as in Table3.

Figure 2: Relative prices of CPIX components to CPIX: services



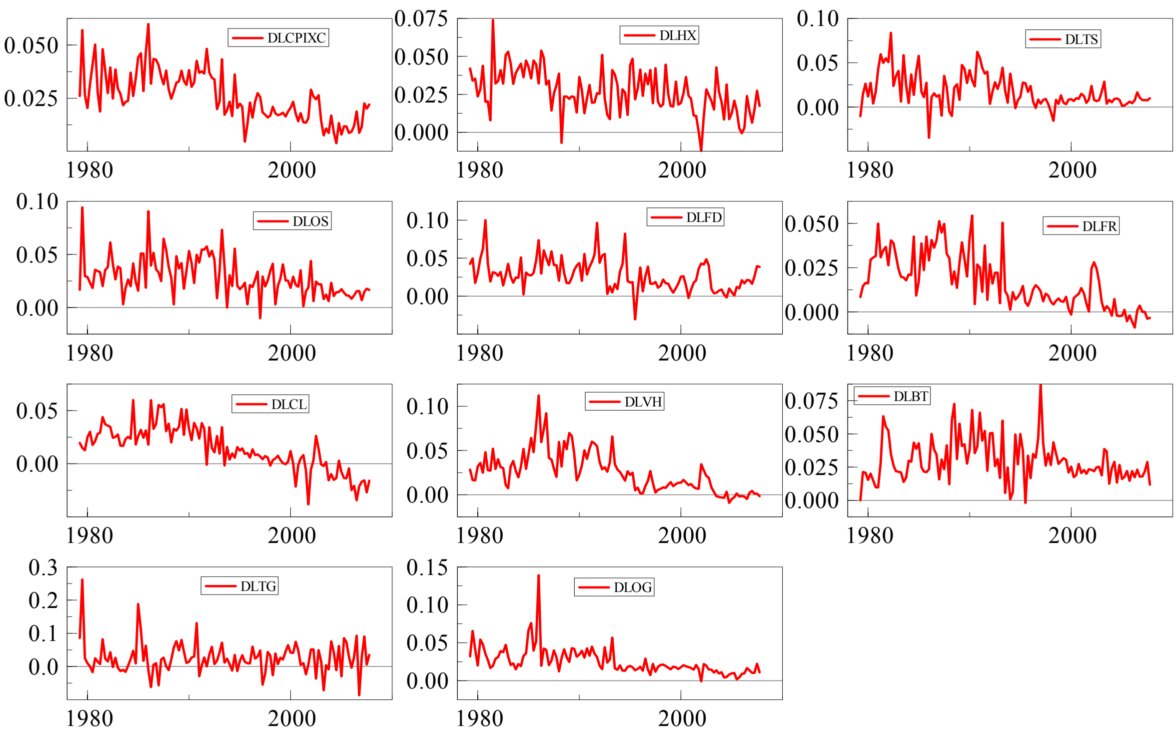
Notes: RAT refers to the ratio of the component to total CPIX, definitions as in Table 3.

Figure 3: CPIX aggregate and subindices (in logarithms)



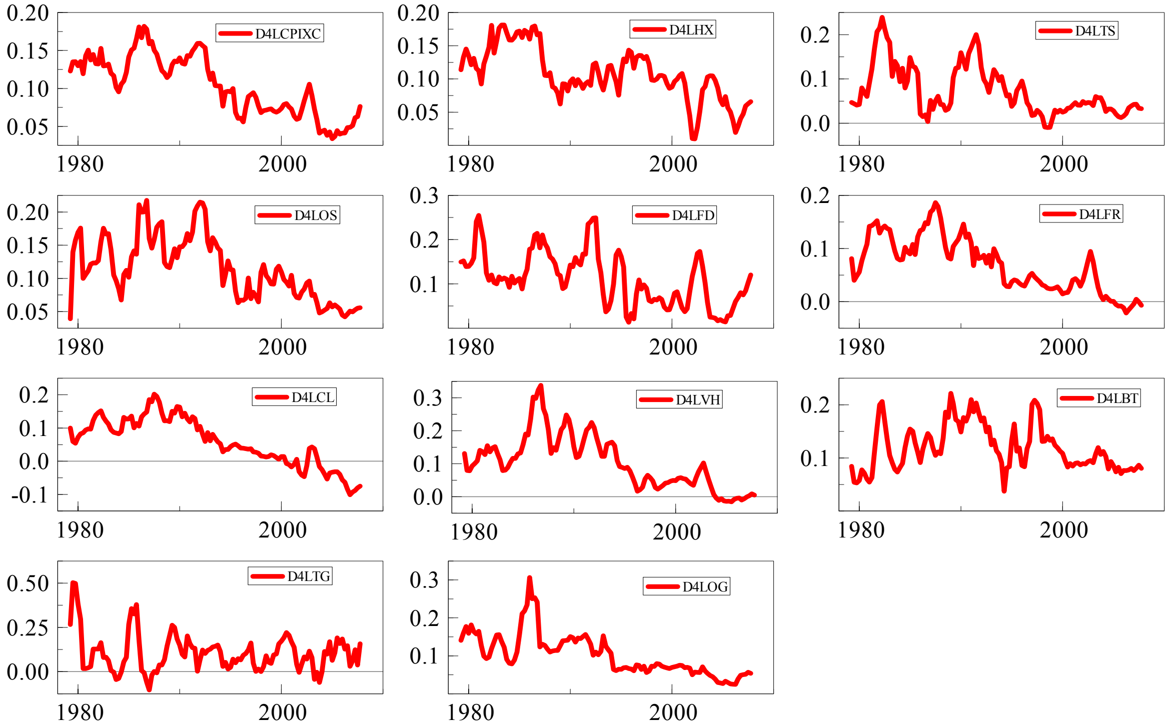
Notes: prefix L=log, definitions as in Table 3.

Figure 4: First differences of CPIX aggregate and subindices (in logarithms)



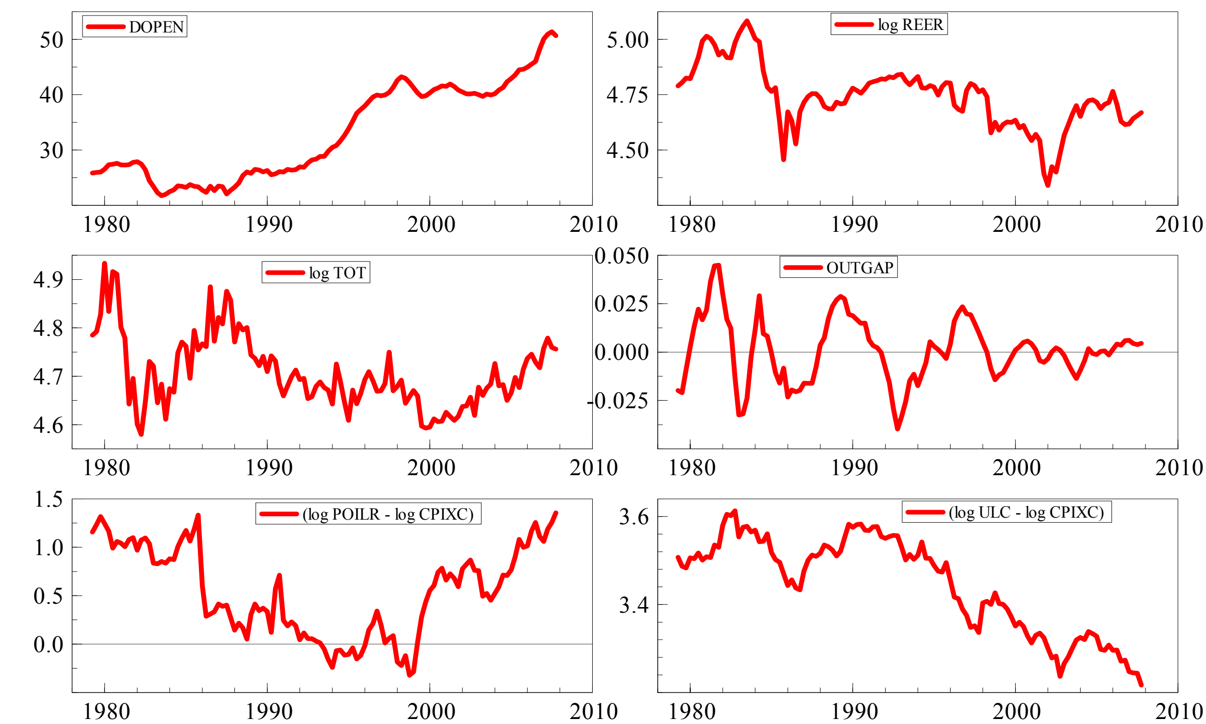
Notes: prefix DL=Δlog, definitions as in Table 3.

Figure 5: Annual differences of CPIX aggregate and subindices (in logarithms)



Notes: prefix D4L=$\Delta_4$log, definitions as in Table 3.

Figure 6: Long-run variables relevant in the aggregate CPIX equation of *GUM2*



Notes: DOPEN is an index. All other variables are in log form, see definitions in Table 3.

APPENDIX 1:

Equations selected by Autometrics for *GUM1*:

The variable definitions are as in Table 3.

OLS $\Delta_4$log CPIXC(+4) constant, $\Delta_4$log CPIXC(-4), $\Delta_2$log ULC, $\Delta_2$log WPDTOT(-2), $\Delta_4$log POILR(-4), $\Delta_2$log REER, $\Delta_2$log REER(-2), DOPEN;

OLS Δ4log HX(+4) constant, $\Delta_2$log HX(-2), $\Delta_4$log HX(-4), $\Delta_2$log CPIXC(-2), $\Delta_4$log ULC(-4), $\Delta_2$log WPDTOT(-2), $\Delta_4$log WPDTOT(-4), $\Delta_2$log POILR, ΔRCURBAL, Δ_2RCURBAL, Δ_2RCURBAL(-2), Δ_4RCURBAL(-4), $\Delta_2$log REER(-2), DOPEN, Δ_2OUTGAP(-2), $\Delta_2$log TOT;

OLS $\Delta_4$log TS(+4) constant, Δ2log ULC(-2), $\Delta_4$log ULC(-4), $\Delta_2$log POILR, $\Delta_2$log POILR(-2), $\Delta_4$log POILR(-4), Δ_2RCURBAL, Δ_2RCURBAL(-2), $\Delta_4$log REER(-4), DOPEN, $\Delta_4$log TOT(-4), $\Delta_4$log IMPD(-4);

OLS $\Delta_4$log OS(+4) constant, $\Delta_2$log OS, $\Delta_2$log OS(-2), $\Delta_2$log CPIXC, $\Delta_2$log CPIXC(-2), $\Delta_2$log ULC, $\Delta_2$log WPDTOT, $\Delta_2$log REER, Δ2log REER(-2), $\Delta_2$log IMPD(-2);

OLS $\Delta_4$log FD(+4) constant, $\Delta_2$log FD(-2), $\Delta_2$log CPIXC(-2), Δlog ULC, $\Delta_2$log WPDTOT, $\Delta_2$log WPDTOT(-2), $\Delta_4$log POILR(-4), Δ_2RCURBAL, Δ_4OUTGAP(-4), $\Delta_2$log TOT(-2), Δlog IMPD, $\Delta_4$log IMPD(-4);

OLS $\Delta_4$log FR(+4) constant, Δlog FR, $\Delta_4$log FR(-4), Δlog CPIXC, $\Delta_2$log ULC, $\Delta_2$log WPDTOT(-2), $\Delta_4$log WPDTOT(-4), Δ_4RCURBAL(-4), $\Delta_2$log REER, $\Delta_2$log REER(-2), DOPEN, $\Delta_2$log IMPD, $\Delta_2$log IMPD(-2), $\Delta_4$log IMPD(-4);

OLS $\Delta_4$log CL(+4) constant, $\Delta_4$log CL(-4), $\Delta_4$log CPIXC(-4), $\Delta_4$log WPDTOT(-4), $\Delta_2$log POILR(-2), $\Delta_4$log POILR(-4), Δ_2RCURBAL, Δ_2RCURBAL(-2), Δ_4RCURBAL(-4), $\Delta_2$log REER, $\Delta_2$log REER(-2), $\Delta_4$log REER(-4), DOPEN, Δ_4OUTGAP(-4), Δlog IMPD, $\Delta_4$log IMPD(-4);

OLS $\Delta_4$log VH(+4) constant, Δlog VH, Δlog ULC, $\Delta_2$log ULC, $\Delta_2$log ULC(-2), $\Delta_4$log ULC(-4), $\Delta_2$log POILR(-2), $\Delta_4$log POILR(-4), $\Delta_2$log REER, $\Delta_2$log REER(-2), $\Delta_4$log REER(-4), DOPEN, ΔOUTGAP, Δ_2OUTGAP, $\Delta_2$log TOT(-2), $\Delta_4$log TOT(-4), Δlog IMPD, $\Delta_2$log IMPD(-2);

OLS $\Delta_4$log BT(+4) constant, Δlog BT, $\Delta_4$log BT(-4), $\Delta_4$log CPIXC(-4), $\Delta_2$log ULC, $\Delta_4$log WPDTOT(-4), Δlog POILR, Δ_2RCURBAL, Δ_2RCURBAL(-2), $\Delta_2$log REER, Δ2log REER(-2), DOPEN, ΔOUTGAP, Δ_2OUTGAP(-2), Δ_4OUTGAP(-4), $\Delta_4$log TOT(-4), $\Delta_2$log IMPD, $\Delta_2$log IMPD(-2);

OLS $\Delta_4$log TG(+4) constant, $\Delta_4$log TG(-4), $\Delta_4$log CPIXC(-4), $\Delta_2$log ULC, $\Delta_2$log ULC(-2), $\Delta_4$log ULC(-4), $\Delta_2$log WPDTOT, Δlog POILR, Δ_2RCURBAL, Δ_2RCURBAL(-2), $\Delta_2$log REER(-2), $\Delta_4$log REER(-4), DOPEN, Δ_2OUTGAP(-2), $\Delta_2$log TOT, $\Delta_2$log TOT(-2), $\Delta_2$log IMPD(-2);

OLS $\Delta_4$log OG(+4) constant, $\Delta_4$log ULC(-4), $\Delta_2$log WPDTOT, $\Delta_2$log POILR, $\Delta_2$log POILR(-2), $\Delta_4$log POILR(-4), $\Delta_2$log REER, $\Delta_2$log REER(-2), DOPEN, Δ_4OUTGAP(-4), $\Delta_4$log TOT(-4);

Equations selected by Autometrics for *GUM2*:

The variable definitions are in Table 3. Nomenclature for error correction terms: e.g. (log POILR- log CPIXC).

OLS $\Delta_4$log CPIXC(+4) constant, Δlog ULC, $\Delta_2$log ULC, $\Delta_2$log ULC(-2), $\Delta_4$log ULC(-4), $\Delta_2$log WPDTOT, $\Delta_2$log POILR, Δ_2RCURBAL, Δ_2RCURBAL(-2), Δlog REER, DOPEN, Δ_2OUTGAP, Δ_2OUTGAP(-2), Δ_4OUTGAP(-4), $\Delta_2$log TOT, Δlog IMPD, $\Delta_4$log IMPD(-4), log REER, LTOT, OUTGAP, (log POILR- log CPIXC), (log ULC- log CPIXC) ;

OLS $\Delta_4$log HX(+4) constant, $\Delta_2$log HX, $\Delta_4$log HX(-4), $\Delta_2$log CPIXC, $\Delta_4$log CPIXC(-4), $\Delta_2$log ULC(-2), $\Delta_4$log ULC(-4), $\Delta_4$log WPDTOT(-4), $\Delta_4$log POILR(-4), ΔRCURBAL, Δ_4RCURBAL(-4), $\Delta_2$log REER, $\Delta_4$log REER(-4), DOPEN,SPLIT854, OUTGAP,RCURBAL, $\Delta_2$log HPMED, $\Delta_2$log HPMED(-2), $\Delta_4$log HPMED(-4), (log HPRICE- log HX);

OLS $\Delta_4$log TS(+4) constant, $\Delta_2$log TS, $\Delta_2$log TS(-2), $\Delta_4$log TS(-4), Δlog CPIXC, $\Delta_2$log ULC, $\Delta_2$log WPDTOT, $\Delta_4$log WPDTOT(-4), $\Delta_2$log POILR, $\Delta_2$log POILR(-2), $\Delta_4$log POILR(-4), Δ_2RCURBAL, Δ_2RCURBAL(-2), DOPEN, Δ_2OUTGAP, Δ_2OUTGAP(-2), $\Delta_2$log TOT, $\Delta_2$log TOT(-2), $\Delta_4$log IMPD(-4), SPLIT854, RCURBAL, (log POILR- log TS), (log ULC- log TS);

OLS $\Delta_4$log OS(+4) constant, Δlog CPIXC, $\Delta_2$log CPIXC, $\Delta_2$log CPIXC(-2), $\Delta_4$log CPIXC(-4), Δlog WPDTOT, $\Delta_2$log WPDTOT, $\Delta_2$log WPDTOT(-2), $\Delta_4$log WPDTOT(-4), $\Delta_2$log POILR, $\Delta_2$log POILR(-2), $\Delta_2$log REER, Δ_2OUTGAP, $\Delta_2$log IMPD(-2), SPLIT854, SPLIT951, DOPEN, log REER, RCURBAL, (log POILR- log OS), (log CPIXC- log OS), (log ULC- log OS);

OLS $\Delta_4$log FD(+4) constant, Δlog FD, $\Delta_2$log FD, $\Delta_2$log FD(-2), $\Delta_4$log FD(-4), Δlog CPIXC, $\Delta_2$log ULC, $\Delta_2$log ULC(-2), Δlog WPDTOT, $\Delta_2$log WPDTOT, $\Delta_2$log WPDTOT(-2), $\Delta_2$log POILR, $\Delta_2$log POILR(-2), $\Delta_4$log POILR(-4), ΔRCURBAL, Δ_2RCURBAL, Δ_4OUTGAP(-4), Δlog TOT, $\Delta_2$log TOT(-2), $\Delta_4$log TOT(-4), SPLIT854, SPLIT951, LTOT, RCURBAL, (log ULC- log FD), (log POILR- log FD), (log CPIXC- log FD), (log WPFD- log FD), $\Delta_2$log WPFD(-2);

OLS $\Delta_4$log FR(+4) constant, $\Delta_2$log FR, $\Delta_2$log FR(-2), $\Delta_4$log FR(-4), $\Delta_2$log CPIXC(-2), $\Delta_4$log CPIXC(-4), Δlog ULC, $\Delta_2$log ULC(-2), $\Delta_4$log ULC(-4), $\Delta_2$log WPDTOT, $\Delta_4$log WPDTOT(-4), $\Delta_2$log POILR, $\Delta_2$log POILR(-2), $\Delta_4$log POILR(-4), $\Delta_2$log REER, Δ_2OUTGAP, Δ_2OUTGAP(-2), $\Delta_2$log TOT, $\Delta_2$log TOT(-2), $\Delta_2$log IMPD, SPLIT854, log REER, LTOT, OUTGAP, (log IMPD- log FR), $\Delta_2$log WPMET, $\Delta_2$log WPMET(-2), DOPEN;

OLS $\Delta_4$log CL(+4) constant, Δlog CL, $\Delta_2$log CL, $\Delta_2$log CL(-2), $\Delta_2$log CPIXC(-2), $\Delta_2$log WPDTOT(-2), Δlog POILR, $\Delta_2$log POILR(-2), $\Delta_4$log POILR(-4), Δ_2RCURBAL, Δ2RCURBAL(-2), $\Delta_2$log REER(-2), $\Delta_4$log REER(-4), Δ_2OUTGAP(-2), Δ_4OUTGAP(-4), $\Delta_2$log IMPD, $\Delta_2$log IMPD(-2), $\Delta_4$log IMPD(-4), SPLIT854, LTOT, OUTGAP, (log CPIXC- log CL), Δlog WPCL, $\Delta_2$log WPCL, $\Delta_2$log WPCL(-2), DOPEN;

OLS $\Delta_4$log VH(+4) constant, Δlog VH, $\Delta_2$log CPIXC(-2), $\Delta_4$log CPIXC(-4), $\Delta_2$log ULC(-2), Δlog WPDTOT, $\Delta_2$log WPDTOT, $\Delta_2$log WPDTOT(-2), Δlog POILR, $\Delta_2$log POILR, $\Delta_2$log POILR(-2), $\Delta_4$log POILR(-4), Δlog REER, $\Delta_2$log REER(-2), ΔOUTGAP, Δ_2OUTGAP, Δ_4OUTGAP(-4), Δlog TOT, $\Delta_4$log TOT(-4), $\Delta_2$log IMPD, $\Delta_2$log IMPD(-2), SPLIT854, SPLIT951, log REER, LTOT, OUTGAP, RCURBAL, (log CPIXC- log VH), (log WPMACH- log VH), Δlog WPMACH, $\Delta_2$log WPMACH, DOPEN;

OLS $\Delta_4$log BT(+4) constant, $\Delta_4$log BT(-4), $\Delta_2$log CPIXC, $\Delta_2$log CPIXC(-2), $\Delta_2$log ULC, $\Delta_2$log WPDTOT, $\Delta_2$log WPDTOT(-2), $\Delta_4$log WPDTOT(-4), $\Delta_2$log POILR, $\Delta_2$log POILR(-2), $\Delta_4$log POILR(-4), Δ_2RCURBAL, Δ_2RCURBAL(-2), Δlog REER, $\Delta_2$log REER, $\Delta_2$log REER(-2), ΔOUTGAP, Δ_2OUTGAP, Δ_2OUTGAP(-2), Δ_4OUTGAP(-4), Δlog TOT, $\Delta_2$log WPBT, $\Delta_2$log WPBT(-2), $\Delta_4$log WPBT(-4), SPLIT854, SPLIT951, DOPEN, log REER, OUTGAP, (log WPDTOT- log BT);

OLS $\Delta_4$log TG(+4) constant, $\Delta_2$log TG, $\Delta_4$log TG(-4), Δlog WPDTOT, $\Delta_2$log WPDTOT, Δlog POILR, $\Delta_2$log POILR(-2), Δ_2RCURBAL, Δ_2RCURBAL(-2), Δ_4RCURBAL(-4), ΔOUTGAP, Δ_2OUTGAP(-2), $\Delta_2$log TOT, $\Delta_2$log TOT(-2), $\Delta_4$log TOT(-4), $\Delta_2$log IMPD(-2), SPLIT854, SPLIT951, $\Delta_4$log WPMACH(-4), (log ULC- log OS);

OLS $\Delta_4$log OG(+4) constant, $\Delta_2$log OG(-2), $\Delta_4$log OG(-4), $\Delta_2$log ULC(-2), $\Delta_2$log WPDTOT(-2), $\Delta_2$log POILR, $\Delta_2$log POILR(-2), $\Delta_4$log POILR(-4), Δlog REER, $\Delta_4$log REER(-4), Δ_2OUTGAP, Δ_4OUTGAP(-4), $\Delta_2$log IMPD(-2), $\Delta_4$log IMPD(-4), SPLIT854, log REER, OUTGAP, (log WPMTOT- log OG), $\Delta_2$log WPMTOT, $\Delta_2$log WPMTOT(-2), $\Delta_4$log WPMTOT(-4), DOPEN;

APPENDIX 2: Equations for aggregate $\Delta_4$log CPIX (+4), originally selected for *GUM1* and *GUM2* up to 2002q2, and then run over the full sample to 2007q1

***GUM1*:**		
	Coefficient	***t-HACSE***
$\Delta_4$log CPIXC(-4)	-0.165	-1.84
$\Delta_2$log ULC	0.180	2.59
$\Delta_2$log WPDTOT(-2)	0.292	1.83
D4LPOILR(-4)	0.0246	3.71
$\Delta_2$log REER	-0.119	-5.9
$\Delta_2$log REER(-2)	-0.0763	-3.88
DOPEN	-0.004	-6.82
Constant	0.224	7.59
Diagnostics		
Equation standard error	0.01628	
Adjusted R^2	0.842	
DW	0.67	
Normality test: $Chi^2(2)$	0.705 [0.703]	
Hetero test: F(14,89)	2.23 [0.0122]*	
RESET test: F(1,103)	0.564 [0.455]	

***GUM2*:**		
	Coefficient	***t-HACSE***
$\Delta_2$log ULC	-0.197	-4.6
$\Delta_2$log ULC(-2)	-0.260	-4.33
$\Delta_4$log ULC(-4)	-0.163	-4.32
$\Delta_2$log POILR	-0.0194	-2.33
Δ_2RCURBAL(-2)	-0.101	-2.98
DOPEN	-0.00225	-4.55
Δ_2OUTGAP	-0.743	-3.49
Δ_2OUTGAP(-2)	-0.620	-3.98
Δ_4OUTGAP(-4)	-0.451	-2.84
$\Delta_2$log TOT	-0.163	-4.96
Δlog IMPD	0.0639	2.07
logREER	-0.140	-8.73
logTOT	0.221	6.87
OUTGAP	0.924	4.87
ECM term: (log POILR- log CPIXC)	0.0240	6.98
Constant	-1.44	-6.26
ECM term: (log ULC- log CPIXC)	0.368	7.94
Diagnostics		
Equation standard error	0.01249	
Adjusted R^2	0.915	
DW	1.22	
Normality test: Chi^2 (2)	0.215 [0.898]	
Hetero test: F(14,89)	0.814 [0.734]	
RESET test: F(1,103)	1.140 [0.288]	

Notes: The variable definitions are as in Table 3. Statistics are reported to three significant figures.

APPENDIX 3: The specifics of the equilibrium correction model equations

Services components equations

For the *house price component*, openness and a split trend from the end of 1985 are relevant. Openness has the expected positive sign discussed above. The negative split trend could reflect the fact that with financial liberalisation from the mid-1980s, access to mortgage credit became easier for potential owner-occupiers, suggesting a fall in demand for rental accommodation and so a slower rate of increase in rents. Housing costs excluding mortgage interest are an amalgam of rents, costs of repairs and maintenance and domestic staff costs. Some of these are likely to follow CPIX, and changes in CPIX inflation play a role, along with changes in unit labour costs and oil prices. The equilibrium correction with respect to house prices, also likely to feed into rents, is important, and there are long-run effects in excess demand indicators, the output gap and current account balance.

The relative price of *transport services* shows a distinct downward trend from the mid-1980s, probably attributable to attempts to lower the costs of publicly-owned bus and other transport in the difficult political climate after 1984, and then deregulation of bus and taxi services after the elections of 1994. The negative split trend from 1985 captures the changes in the administered prices of transport, for which we do not have figures. Openness has the positive sign expected for services as relative prices to tradeable goods have risen with increased openness. There are two significant equilibrium correction terms, suggesting that, in the long run, transport services prices depend on oil prices and on unit labour costs in manufacturing, both with long lags. The other factor in the long run is the current account balance to GDP. The dynamics reflect an inflationary impetus from past transport prices, import prices, the terms of trade and the output gap.

For *other services*, openness has the expected positive sign consistent with the relative non-tradability of this category. The relative price of other services shows a steep rise from 1985 with the slope reduced from the mid-1990s. The two split trends capture this effect, the first positive, and the second negative, but smaller in absolute size than the first. As with "other goods", this sector encompasses a broad range of sub-components, with medical, communication and education services having the highest weights. The annual average increase in the price increases of the other services component exceeded the total inflation rate after 1990. This can be attributed to the decision to extend and improve key services to all population groups. Three equilibrium correction terms appear, linking "other services" prices with CPIX, unit labour costs and oil prices (with long lags for the last). Other terms in the long-run solution are the real exchange rate and the current account balance to GDP.

Goods components equations

Turning to the *food* component, SA has a substantial agricultural sector, and production is subject to weather shocks, with inflationary consequences. For the large fraction of the population on low incomes, there are important welfare consequences, as maize is the major food staple. In 1987, the maize marketing board was abolished, with other marketing boards abolished by the early 1990s. Under the more open economy in the 1990s and with the removal of trade sanctions, food prices in SA became more subject to international influences. Few food products are imported directly, but the depreciating currency induced rising transport cost and import tariffs in these. In 1996, the South African Futures Exchange began operation, further increasing the influence of foreign prices and the exchange rate. After a sharp currency depreciation in late 2001, maize prices rose at record rates, trading at import parity prices, due to high regional demand in a drought.

Several equilibrium correction price terms are significant, linking the CPI food price component with the wholesale food price index, overall CPIX, oil prices and unit labour costs, with long lags in the latter three. Other long run terms include the terms of trade, where enhanced demand from trade booms elevates the prices received for agricultural output, and the current account balance to GDP. The two split trends reflect structural changes in the food inflation process linked to the removal of the marketing boards, the first trend positive, and the second negative and similar in absolute size to the first.[19] The dynamics in the equation also includes lagged rates of change in the food CPI component and changes in the overall domestic wholesale price.

The upward trend in the relative price of food in SA began in 1970, by contrast with the corresponding relative price in the U.S., which has shown a general downward trend since 1980. Perhaps relative wages of unskilled workers, such as those employed in retailing, have risen in SA, but declined in the U.S. The increased openness of the economy in the 1990s, leading to rapid productivity gains in the manufacturing sector and competitive pressures on prices of tradeables, may plausibly have had a smaller effect on food prices so raising their relative price. The proportion of processed food and meals taken outside the home has increased over time in SA, and these items are more expensive but presumably reflect a quality improvement. It has also been argued that the proliferation of new shopping centres in SA has encouraged retailers to open new stores with existing sales simply spread across an increasing number of outlets, thus raising costs. More detailed comparisons with other countries and a check on the procedures used by *Statistics South Africa* to take account of new goods, and quality change in the food sector, needs to be undertaken, along with a study of retail margins and the evolution of concentration ratios in retailing.

The *furniture* price component shows the relevance of openness and a negative split trend from the end of 1985, attributable to more international competition and a combination of technological cost reductions and quality improvements. There is an equilibrium correction of the price index for furniture to imported goods with long lags, and a strong real exchange rate effect, as expected for this tradable component. The terms of trade and output gap matter in the long-run, both with long lags. The dynamics include an inflationary impetus from changes in the overall CPIX index and in unit labour costs, and effects from both the overall wholesale price index and the specific index for metals.

The relative price of *clothing and footwear* exhibits a similar downward trending pattern to that of furniture and equipment, and for similar reasons: productivity growth, and especially greater openness to competitive trade from 1990 onwards. Both the (negative) openness indicator and the negative split trend from 1985 capture these changes. The long run equilibrium correction term links clothing prices with the wholesale price for clothing. The output gap (with long lags) and terms of trade also matter in the long-run. The dynamics in the equation include lagged rates of change in the clothing and footwear CPI component (indicating a strong tendency to correcting previous overshoots); and the inflationary effect of the lagged six-monthly change in overall CPIX.

Turning to the *vehicles* component, there was a sharp increase in relative vehicle prices from the mid-1980s to the mid-1990s (Figure 2). Prices stabilised from 2000, after declining for about five years. Tariffs on built-up vehicles exceeded 100 percent from the early 1980s to the early 1990s, were reduced from 1993/4 and then more sharply thereafter, and have since fallen to 38 percent. Local content requirements were tightened in 1984 probably raising prices. These institutional facts are consistent with the two split trends, with a positive effect from 1985 and a larger absolute negative effect from the mid-1990s. Openness also matters in the expected direction for a tradable good. The extent of the relative price rise between the mid 1980s and 1993 raises questions about whether adequate allowance was made for quality improvements in the CPI vehicles component. A further consideration is that the wholesale price index for imports may not fully compensate for the rand's weakness against the yen and Deutsche mark: these currencies experienced a structural strengthening against the U.S. dollar for 1986-94 (most vehicle imports originate in Japan and Germany).

The vehicles equation incorporates equilibrium correction terms suggesting that, in the long run, vehicle prices depend on the CPIX and on wholesale machinery prices. The other factors in the long run solution are the output gap and current account balance to GDP, indicating a response to excess demand, and the real exchange rate and terms of trade. The dynamic terms in the model include lags of rates of change of vehicle prices, and the inflationary effects of oil prices, and overall wholesale prices and the real exchange rate.

The relative log ratio of *beverages and tobacco* prices moved sharply upwards from about 1987, having declined during the previous fifteen years. The two positive split trends with similar slopes in the selected model are consistent with indirect tax effects. The cheapening of tobacco and alcohol products through the expansion of local manufacturing capacity in the 1970s was rapidly reversed with higher taxation, especially following election of the ANC government in 1994, when there was a strong rise in duties on cigarettes, tobacco and alcoholic beverages. Openness has the expected positive sign, with these goods largely non-traded in the SA context. One equilibrium correction term is significant, linking beverage and tobacco prices with total domestic wholesale prices, the price dynamics suggesting long lags in the ECM. The other terms in the long-run solution are the output gap, suggesting some impact from excess demand pressures on prices; and the real exchange rate. The dynamics include inflationary effects from oil prices and overall CPIX, and effects from the wholesale price in beverages and tobacco, the current account balance and the real exchange rate.

The relative price of *transport goods* fell sharply in the mid-1980s and gradually rose from about 1998, perhaps due to an increase in fuel duties. This is well captured by the two split trends, the first negative and the second positive. The very different pattern from the "vehicles" sub-component is interesting. Presumably there would have been low tariffs on parts to encourage local assembly and high tariffs on finished vehicles. The local contents requirements in the 1980s and 1990s may have increased investment in parts manufacture, bringing economies of scale. Perhaps the substitution of cheaper local parts for expensive imported parts brought down prices. However, the index is dominated by petrol and diesel, and rand oil prices are important in the dynamics, as are the terms of trade. There is also an effect from changes in the current account surplus to GDP ratio and in the output gap, excess demand indicators, and overall wholesale prices. The transport goods equation incorporates an equilibrium correction term in unit labour costs.

The relative price of *other goods* shows a declining trend from the mid-1980s onwards. As with "other services", this category covers a wide group of goods, with imported goods, or goods using foreign imports well represented, suggesting the likely importance of the exchange rate. One equilibrium correction term appears, linking "other goods" prices with manufacturing wholesale prices, with the price dynamics indicating long lags. Other terms in the long-run solution are the output gap and the real exchange rate. In the dynamics, there are inflationary effects from lagged changes in other goods prices, from overall wholesale prices and oil prices, and import prices.

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[1] Hendry and Hubrich (2006) document the main contributions to the theoretical literature on aggregation versus disaggregation in forecasting as Grunfeld and Griliches (1960), Kohn (1982), Lütkepohl (1984, 1987), Pesaran, Pierse and Kumar (1989), Van Garderen, Lee and Pesaran (2000) and Granger (1990).

[2] From January, 2009, the targeted measure of CPI has been redefined and rebased, see below.

[3] Given processing delays, the 1990 weights were applied from August 1991 to December 1996, the 1995 weights from January 1997 to December 2001, and the 2000 weights from January 2002. In earlier years, the weights were held constant for 1960 to 1977, January 1978 to October 1987, and November 1987 to July 1991.

[4] Weights in CPIX are obtained from the weights in the CPI by scaling by (100-the weight on the mortgage interest)/100; the mortgage interest weight in CPI is given in Table 2.

[5] With their CPI "metropolitan" weights: "Fuel and power" (3.49), "Household consumables" (1.25), "Reading matter" (0.39), "Recreation :and entertainment equipment" (2.44). "Water" (1.37), "Personal care products" (3.06), "Medical care and health products" (2.77) and "Other goods" (0.54).

[6] With their CPI "metropolitan" weights: "Household services" (0.09), "Communication" (2.98),"Education" (3.48), "Medical services" (4.38), "Personal care services" (0.61) and "Other services" (2.78).

[7] However, our prior on this sign is weak, since an improvement in the terms of trade may cause the exchange rate to appreciate and so have a disinflationary effect.

[8] The real exchange rate (defined to increase with appreciation) is, in effect, another relative price term: of trade-weighted foreign wholesale price indices converted to local currency, relative to SA's wholesale price index.

[9] At a sectoral level, indirect tax increases are likely rapidly to feed through into consumer prices, and hence we would not expect significant effects of tax rates in a four-quarter-ahead approach. However, there is scope for separately developing forecasting models for indirect tax rates, which could take into account fiscal deficits.

[10] For example, the effect of business costs increasing when interest rates rise, contrasts with the disinflationary effect via lower demand pressure, exchange rate appreciation, or inflation expectations. The 'cost channel' of monetary policy via the real prime rate is controversial for central bankers and has been the subject of a significant literature, see Barth and Ramey (2001). A related mechanism by which higher interest rates may raise subsequent inflation is via the effect of high interest rates on investment and bankruptcies. These reduce capacity and so may increase inflation in subsequent upturns.

[11] For less tradable goods and services, the price relative to the CPI may increase with increases in trade liberalization, implying a positive effect.

[12] Potentially, interaction effects could be important with measures of institutional change. For example, if the cost channel discussed above works through the capital stock, the effect may have been overshadowed in more recent years by the opening of the economy to international trade and capital flows.

[13] For recursive out of sample forecasting, this has the advantage over using STOCHTR in that STOCHTR does not have to be re-estimated for every new observation.

[14] This means that data on the four-quarter inflation rate in the dependent variable span 1980q2 to 2003q2 in the estimation period, using data on the regressors for 1979q2 to 2002q2 to fit the model. For the forecast period, data on the dependent variable span 2003q3 to 2007q4, and on the regressors, 2002q3 to 2006q4.

[15] Autometrics is an objective and easily reproducible tool, not affected by the subjective choices of the modeller. 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, heteroscedasticty, including a test of 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.

[16] The individual equations are not reported in full for brevity.
[17] The long lags are indicated by negative delta effects in the relevant price variable, equivalent to lagging the equilibrium correction terms.
[18] To illustrate for the univariate case, with a lag up to nine quarters for each of the inflation components (Model 5), the RMSFE for the indirect forecast is 0.0318, as indicated in Table 4. The Schwarz B.I.C. information criterion selects an optimal lag length of three, resulting in a RMSFE of 0.0351. Aron and Muellbauer (2010) find that for US inflation, models selected on the basis of B.I.C. forecast less well both in the univariate and multivariate contexts than models using parsimonious longer lags to obtain parsimony.
[19] We do not use dummy variables for the various drought episodes when supply shortages drove up prices, nor are the subtleties concerning import parity pricing post 1996 specifically addressed in our model.