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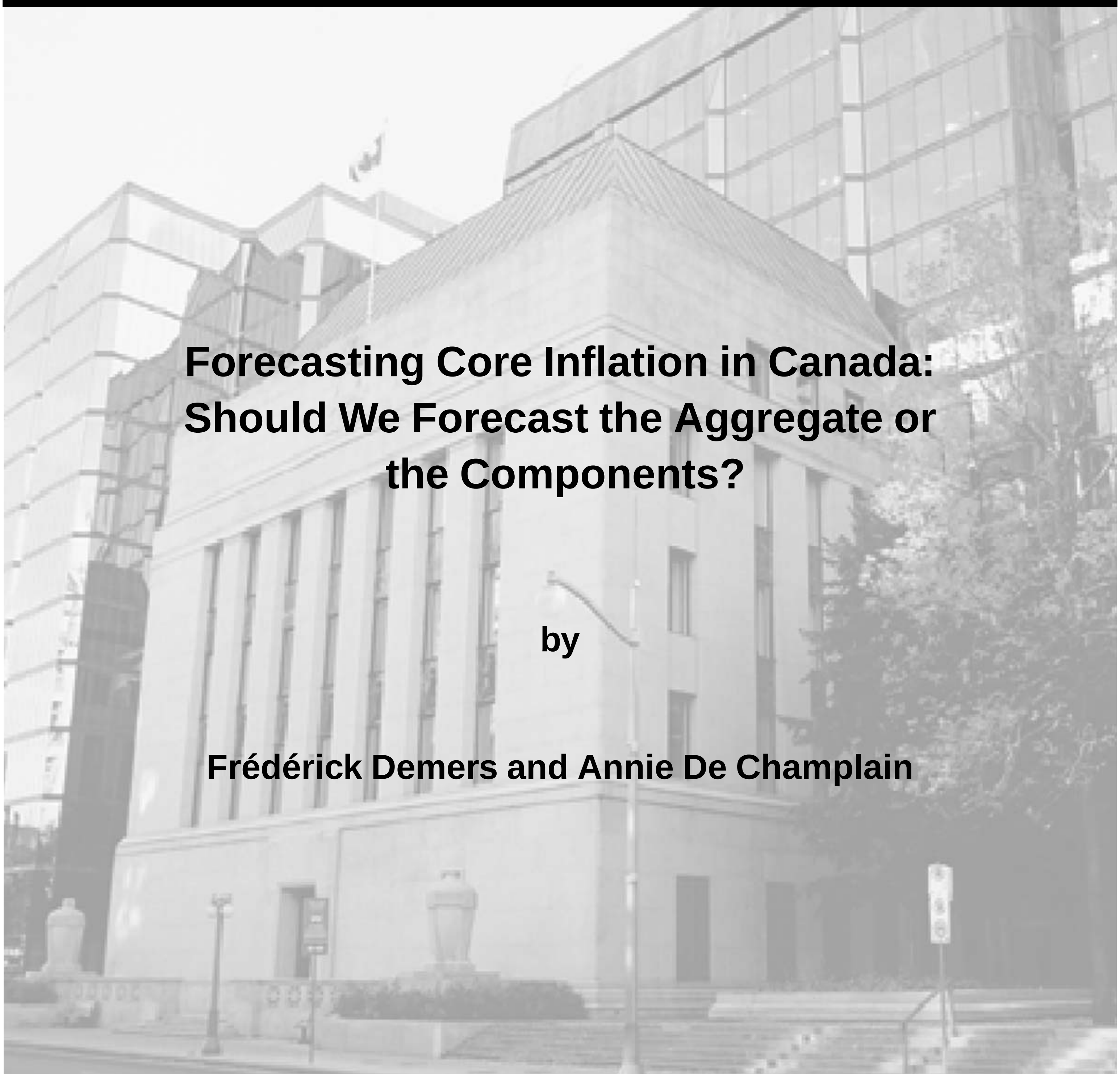

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Abstract

The authors investigate the behaviour of core inflation in Canada to analyze three key issues: (i) homogeneity in the response of various price indexes to demand or real exchange rate shocks relative to the response of aggregate core inflation; (ii) whether using disaggregate data helps to improve the forecast of core inflation; and (iii) whether using monthly data helps to improve quarterly forecasts. The authors show that the response of inflation to output-gap or real exchange rate shocks varies considerably across the components, although the average response remains low; they also show that the average response has decreased over time. To forecast monthly inflation, the use of disaggregate data is a significant improvement over the use of aggregate data. However, the improvements in forecasts of quarterly rates of inflation are only minor. Overall, it remains difficult to properly model and forecast monthly core inflation in Canada.

JEL classification: E37, C5
Bank classification: Econometric and statistical methods; Inflation and prices

Résumé

Les auteurs étudient le comportement de l'inflation fondamentale au Canada en visant un triple objectif : i) examiner l'homogénéité de la réaction de divers indices de prix aux chocs de demande ou de taux de change réel par rapport à la réaction de l'inflation fondamentale agrégée; ii) déterminer si l'utilisation de données désagrégées permet de mieux prévoir l'inflation fondamentale; iii) déterminer si l'emploi de données mensuelles améliore les prévisions trimestrielles. Les auteurs montrent que la réaction de l'inflation aux fluctuations de l'écart de production ou du taux de change réel varie beaucoup d'une composante à l'autre, même si elle demeure faible en moyenne. Ils montrent également que l'ampleur de la réaction moyenne a diminué au fil du temps. Les données désagrégées s'avèrent beaucoup plus utiles que les données agrégées pour anticiper l'inflation mensuelle, mais ne procurent que des avantages limités pour ce qui est des prévisions trimestrielles. Globalement, l'évolution mensuelle de l'inflation fondamentale au Canada demeure difficile à modéliser et à prévoir correctement.

Classification JEL : E37, C5
Classification de la Banque : Méthodes économétriques et statistiques; Inflation et prix

1 Introduction and Motivation

Accurate forecasts of inflation are crucial for central bankers whose primary objective is to keep inflation under control, in particular for central banks operating with an official inflation target, as is the case for Canada, New Zealand, and Sweden, among other countries. Although the literature on forecasting models of inflation is impressive when measured by its size and level of sophistication, traditionally the focus has been oriented towards forecasting the quarterly aggregate price index, whether it is the total aggregate or some measure of trend inflation. A notable exception is Hubrich (2005), who compares the forecasting capacity of various aggregate and disaggregate models of year-over-year European inflation for the period of January 1992 to December 2001. One of her main findings is that there are no gains to be made by looking at disaggregate twelve-month-ahead forecasts for the total price index. Interestingly, when Hubrich considers a measure of trend inflation (i.e., the consumer price index (CPI) excluding unprocessed food and energy prices), she finds that forecasting from the disaggregates outperforms the forecasts from the aggregate CPI. This, she points out, could be explained by the difficulty associated with correctly modelling or forecasting series that are subject to large exogenous shocks, such as oil prices. Benalal et al. (2004), in a study on euro-area inflation, obtain similar results when they compare component-based forecasts, whereas they find no improvement in forecast accuracy when they aggregate country-by-country forecasts.[1] In another study, Jondeau, Le Bihan, and Sédillot (1999) suggest a sectoral approach to analyze monthly French price indexes. Despite the interesting and innovative features of their approach, they provide little support for such a forecasting strategy, other than to illustrate the different behaviour of each subcomponent they analyze.

Efficiency gains from disaggregation have also been studied in a slightly different context (i.e., multi-country analysis) by Zellner and Tobias (2000), who examine the usefulness of combining forecasts of GDP growth from various countries. Marcellino, Stock, and Watson (2003) address the same issue, but for inflation forecasts. Demers and Dupuis (2005) find that Canadian GDP growth forecasts can be improved over aggregated models by using multivariate models that use regional GDP growth data.

The usefulness of disaggregated data has always been noted, but in only a cursory manner compared with other topics in time-series analysis. Arguably, the main advantage of using aggregate data is that they require less time than compiling large data sets and analyzing every component available. Furthermore, because they are constructed from a number of

[1] Because Benalal et al. aggregate the forecasts from only four countries, however, they note that this particular result should be viewed with caution.

components, aggregate data are less likely to be significantly affected by measurement error than small indexes, for which the available information might often be more restricted and/or plagued with various sampling issues, such that the amount of noise is increased. Despite these clear and realistic advantages of using aggregate rather than subaggregate data, estimating relationships using aggregate data can be misleading or uninformative, particularly from a policy perspective, where precise parameter estimates are important. Indeed, the high degree of heterogeneity in the different sectors of modern economies could cause them to respond differently to shocks. In extreme cases, some sectors could even respond in opposite ways to a particular shock. Intuitively, it is clear that there are potential gains to be made by carefully investigating the distinctive behaviour of micro-units, so that we can better understand the functioning of the economy, or, in this case, improve our understanding of how prices move across the various sectors that form the (core) CPI, and, ultimately, improve our forecasting accuracy. For instance, it is likely that the prices of services do not react to the same determinants as the prices of (tradable) goods, which might closely depend upon world economic conditions rather than domestic conditions. On this question, Balke and Wynne (2003) and Blis, Klenow, and Kryvtsov (2003) provide empirical examples on U.S. data; they find that prices respond to monetary shocks very heterogeneously across components. From a statistical point of view, the underlying heterogeneity of the data and of the relations may be a source of inefficiency and bias in the estimation of the population parameters when aggregated data are used. The importance of working under the assumption of homogeneity remains empirically subtle, however, because many factors come into play (see, e.g., Clark 2003; Chen and Engle 2004).

At the Bank of Canada, CPI is carefully monitored within a fairly narrow definition (more than 20 subcomponents), although no econometric model is actually used to produce econometric forecasts for each subaggregate. By contrast, the quarterly aggregate measures are systematically forecasted by numerous models. In total, 21 disaggregated core indexes are monitored on a monthly basis, using experts' judgments as the sole guide. Our approach is thus based upon modelling and forecasting the subaggregates of core CPI using component-specific Phillips curves. The rationale is that certain goods and services indexes might exhibit greater sensitivity to demand and supply conditions prevailing in their respective sectors of the economy, while some other sectors might be more sensitive to exchange rate fluctuations. The potential heterogeneity of this side of the economy is examined by estimating Phillips curves that attempt to capture this important property. Hence, because the usual output-gap measures are a proxy for the overall economy, we also analyze the usefulness of sectoral output-gap measures to predict movements of sectoral price indexes.

Although the methodology applied in this paper could well be used to model the overall CPI inflation, our investigation is limited to core price indexes. The eight items that are excluded from the measure of core inflation are not only more volatile than the other consumer prices, but they are often determined by very specific factors, unlike most core components, which are generally believed to depend upon prevailing aggregate demand and supply conditions in the Canadian economy. For instance, Chacra (2002) models Canadian gasoline prices using an equilibrium-correction model, where the price of gasoline depends on the price of crude oil and seasonal patterns. Fruits and vegetables are another good example of a price that is subject to special non-economic factors, such as weather. Because the eight most volatile components require a more sophisticated and careful modelling strategy, this study is limited to modelling and forecasting core prices. Although it is well beyond the scope of this paper, one could generate forecasts of total inflation by combining the forecasts obtained in this paper with those from, say, Chacra's models and building small additional models for the remaining volatile components.

Another important consideration in obtaining accurate forecasts is parameter stability. In recent studies, Demers (2003) and Khalaf and Kichian (2003), among others, report significant non-linearities under the form of discrete or stochastic structural breaks in the parameters of the Canadian Phillips curve, and that the effects of the output gap or the real exchange rate have played no significant role in explaining core inflation in Canada since the 1990s.[2] To account for this important feature of the data, the micro Phillips curves considered in this study also allow for the presence of an unknown single structural break.[3]

To select the lag length, results from three criteria are compared. Overall, pseudo out-of-sample forecasts of more than 200 different models are compared, built from random-walk, autoregressive (AR), and Phillips-curve (ARX) models. For the ARX models, we also compare the results when a structural break is allowed (ARX-K). Compared with Hubrich (2005), who considers only five subaggregates using a shorter sample, our study compares two levels of disaggregation: namely, 6 and 19 components.

This paper analyzes three key issues: (i) the potential heterogeneity in the response of various price indexes to aggregate demand and supply conditions or real exchange rate shocks relative to the response of aggregate core inflation; (ii) whether using disaggregate

[2] As with most of the literature on this topic, both Demers (2003) and Khalaf and Kichian (2003) use quarterly data.

[3] Although other types of non-linear models, such as threshold or Markov-switching models, have been shown to provide a good approximation of the Canadian inflation process (e.g., Demers 2003), these sophisticated models are not used: they would be too difficult to operate on such a large data set and on a monthly basis. They generally require a large amount of analysis to validate every single estimate provided by them, owing to the numerical optimization difficulties encountered.

data helps to improve the forecast of core inflation, as in Hubrich (2005); and (iii) whether using monthly data helps to improve quarterly forecasts. Although point (i) is naturally important for central bankers, since it allows them to better gauge the response of inflation to exogenous shocks, points (ii) and, to a lesser extent, (iii) are of greatest interest in this study, and they therefore receive most of our attention and efforts. The monthly data used in this study span from January 1985 to December 2003.

Of course, a significant by-product of this paper is to provide Bank of Canada staff with econometric forecasts of core indexes, made component by component, at monthly and quarterly frequencies.

According to the empirical results of our study, it appears that some significant gains are to be made from using disaggregate models to forecast monthly core inflation. The gains from using monthly, disaggregate data to forecast the quarterly rate of core inflation are moderate and statistically insignificant. For the purpose of forecasting, the relative cost of using such a large set of information appears to provide little value-added; the use of aggregate quarterly data seems to provide core inflation forecasts that are at least as accurate as those obtained by modelling various micro-relations. Despite the lack of statistical support from variants of the Diebold and Mariano (1995) test for equal forecast accuracy, we feel that one-quarter-ahead forecasts from monthly disaggregate models of inflation can still prove to be useful for short-horizon forecasting. In fact, because forecasting by means of the best disaggregated monthly model can improve the root mean squared forecast error (RMSFE) by nearly 10 per cent, the gain in accuracy is most encouraging. It will be interesting to record future forecast errors from the models proposed in this study.

The rest of this paper is organized as follows. Section 2 describes the stochastic behaviour of the data that are used in this study. Section 3 discusses some issues of data aggregation. Section 4 describes the specifications considered in this study. Section 5 reports and briefly discusses the empirical results from the regressions. Section 6 evaluates the out-of-sample forecasts. Section 7 concludes with brief remarks and suggestions.

2 Constructing the Data

In this section, we describe the data used below in our empirical exercise. Because our approach relies on the principles of the Phillips curve, which relates inflation to the output gap and the real exchange rate, the construction of these two series and the appropriate inflation series is necessary.

2.1 Inflation series

The consumer price data analyzed in this study are taken from Canada's CPI. The series of interest is the measure of core inflation, which excludes the eight most volatile components and the effect of changes in indirect taxes, as described by Macklem (2001), expressed at monthly and quarterly frequencies. To construct the subaggregates, we closely follow the working definitions used by Bank of Canada staff. Two levels of disaggregation are used: 6 and 19 categories.[4] Table A1 in the appendix gives the relative weights of the components. The period studied is from January 1985 to December 2003. Because the published consumer price data exhibit important seasonal patterns, the X-11 seasonal filter is used to obtain time series that have no seasonal component. Of course, an ideal approach to model the seasonality of each series would be to follow the methods described by Franses and Paap (2003)—e.g., periodic models—but such an avenue is far beyond the scope of this study and is therefore left for future research.

To maximize the number of observations available, some series are modified in order to share a common starting point: January 1985. Since some of the components that compose the core CPI have been published only since December 1994, these series are linked to similar components that have historical data going back to January 1985. For example, the component Other Owned Accommodation Expenses is linked to Homeowners' Maintenance and Repairs. This method requires that we take into account the relative weights of the components. Four weight changes are observed during the time period of the study: November 1978 to December 1994, January 1995 to December 1997, January 1998 to December 2002, and January 2003 to December 2003.[5] From January 1985 to December 1994, the new series contains information from only the Homeowners' Maintenance and Repairs component, whereas from January 1995 to December 2003 it includes the sum of both indexes and accounts for their respective weights, which vary depending on the time period observed. The same process is applied when the component Fuel, Parts and Supplies for Recreational Vehicles is combined with Other Non-Durable Goods. The latter includes Non-Durable Goods other than Food, Energy, and Tobacco, and Smokers' Supplies and Alcoholic Beverages.

The rate of inflation is approximated by the log difference, multiplied by 100. Figures 1 to 7 depict the monthly log difference of each price index of interest, including the core measure of inflation, denoted as π_t; the subaggregates are denoted as π_{it}, for $i = 1, ..., N$, N

[4] Compared with the actual definitions used by Bank staff, which are based on 21 components, a slight modification was necessary in this study in order to build consistent time series.

[5] In July 2004, another change in the CPI basket was implemented.

being the number of components. Core inflation is then constructed as follows:

$$\pi_t \equiv \sum_{i=1}^{N} \omega_{i,t}\pi_{i,t}, \tag{1}$$

where $\omega_{i,t}$ is the relative weight of the ith component. The time subscript associated with $\omega_{i,t}$ reflects the changing composition of the CPI basket.

Overall, 169 components are used to construct the Canadian CPI basket. These can be combined into 54 components, of which 8 subaggregates are removed for the construction of the core CPI.

As Figures 1 to 7 show, many price series were greatly affected by the introduction of the Goods and Services Tax (GST) in January 1991. For the price-level series, this event simply causes a level shift; but for the inflation series it translates into a one-time blip, generating an *outlier* in the data, which can have a significant impact on parameter estimates. Although no formal test is used to detect outliers in the data, the GST is nevertheless not treated as part of the underlying data-generating process (DGP).[6] Furthermore, there is no consensus on how to best deal with outliers that are discovered in the data (see, e.g., Gregory and Reeves 2001). To minimize the impact on the parameter estimates, the *contaminated* observation is simply replaced with the unconditional mean calculated from the first available period until one period before the introduction of the GST.[7] This method is preferred to using a GST dummy, mainly to reduce the impact of the GST shock on parameter testing and to maintain a parsimonious specification.

2.2 Real exchange rate

To construct the measure of the real exchange rate, the usual definition is used:

$$e_t \equiv E_t \frac{p_t}{p_t^{US}},$$

where E_t is the nominal Can\$/US\$ exchange rate expressed such that a devaluation in the Canadian dollar translates into a decrease of E_t; p_t^{US} is the implicit U.S. GDP deflator; and p_t is the implicit Canada GDP deflator. Because e_t is generally believed to be I(1), the log difference (multiplied by 100) is used without formally testing the order of integration (see, e.g., Demers 2003; and Kichian 2001). Because the implicit price deflator series are available only on a quarterly basis, a cubic extrapolation is used to obtain a monthly real exchange rate series.

[6] On the detection of outliers for non-stationary time series, see Perron and Rodríguez (2003).

[7] The mean is calculated using only this subsample because we believe, a priori, that the mean of the inflation series has changed over time. If this view is incorrect and the mean has, in fact, remained constant over time, then calculating the mean with the full sample would not make any difference.

2.3 Measuring potential output

Although it is a widely used variable in empirical economics, potential output is nevertheless an unobserved theoretical concept that needs to be estimated. There is no clear consensus on how best to estimate potential output and, ultimately, extract the output gap from the level of GDP. Cayen and van Norden (2002) offer a comprehensive review and analysis of the most commonly used econometric methods to estimate the output gap.

We assess the ability of various output-gap measures to forecast the inflation series. First, we use the Bank's measure, which is based on a variant of the Hodrick-Prescott filter (for details, see Butler 1996), as a proxy of aggregate supply and demand conditions. Because this series is available only on a quarterly basis, we use a cubic extrapolation to obtain a monthly series.

Second, we estimate various output-gap measures from the GDP at basic price series, available on a monthly basis since 1981, expressed at annual rates in 1997 constant prices and seasonally adjusted. The aim is to assess the extent to which using sectoral measures can affect the estimated response of inflation to output-gap shocks and, more importantly, to determine whether forecast accuracy can be improved. Therefore, for the components that are believed to be dominantly affected by the demand/supply conditions of a particular sector of the economy, we use the selected output-gap measure.[8] Data from the following sectors are used: Business Goods, Durable Manufacturing Goods, Non-Durable Manufacturing Goods, and Business Services output. To obtain a measure of potential output from these output series, we use a polynomial deterministic function. To ensure that the output-gap measures that are estimated using this approach are stationary, the output series are tested for a unit root using appropriate critical values. The order of the deterministic polynomial function is determined following a general-to-specific strategy, using the longest available sample (i.e., 1981Q1–2003Q4 for the quarterly frequency, and January 1981 to December 2003 for the monthly frequency).[9] The main advantage of using this type of measure is that it allows us to avoid the so-called 'generated regressor' problem (see Pagan 1984). It also allows the trend growth rate of output to slowly change over time. Figure 8 depicts the estimated output-gap measures, at a monthly frequency, and compares them with the QPM measure, which is converted to the monthly frequency. The good approximation of each measure is

[8] The price indexes series are associated with the sectoral measures in a purely ad hoc fashion, following our best judgment, since there are no systematic decision rules for this problem. Table A1 lists the associations.

[9] Recursive output-gap measures were constructed, but they did not provide a satisfying approximation of the business cycle for the first half of the sample. This could be explained mainly by the relatively small sample that is used to estimate the trend level of output (i.e., less than 25 years). Output-gap estimates based on the complete information set are therefore used.

notable, particularly for the goods sector. All alternative measures exhibit a larger variance than the QPM series. The validity of the results obtained using this approach largely depend upon unit-root issues; further details of the estimation and the empirical stochastic process are discussed in section 2.4.

In line with the spirit of this paper, the output-gap measure for the total Business sector, referred to as Total, is obtained by combining the estimated measures of potential output for Business Goods and Services.

All the data sources for the exogenous variables are identified in the appendix (Table A2).

2.4 Testing for a unit root

In this subsection, the stochastic behaviour of the time series is examined to determine whether they can be described as I(0) or I(1) processes, and to determine whether the behaviour of the various components that compose core inflation differs from the behaviour of core inflation itself.[10]

To test for a unit root in each of the inflation series of interest, the simple augmented test of Dickey and Fuller (1979; ADF) is used, in addition to the two-step test procedure proposed by Perron (1997; hereafter P97), with the following specification:

$$x_t = \mu + \theta A_t + \delta B_t + \lambda t + \alpha x_{t-1} + \sum_{j=1}^{p} \phi_j \Delta x_{t-j} + u_t, \tag{2}$$

where u_t is a stochastic innovation, μ is some constant, t is a time trend, and $A_t = \mathbf{1}(t > T_B)$ and $B_t = \mathbf{1}(t = T_B + 1)$ are dummy variables that capture a level shift in the series x_t; the break point (T_B) is selected by the minimization of the t-statistic on α. Perron's test can be used to test the null hypothesis that a time series contains a unit root ($\alpha = 1$) and is subject to a shift in the deterministic trend function at some unknown point in time, while the alternative hypothesis is that the series is I(0) with a break. The test results are reported in Table 1, for both the monthly and quarterly frequencies. Under the null hypothesis of a unit root, the sampling frequency is, of course, irrelevant, but if one is interested in favouring the alternative, the choice of the frequency might play an important role when the estimated root is close to unity but different from it (Perron 1991).

Table 1 shows that the sampling frequency does play an important role in concluding either favourably or against the null hypothesis of a unit root. According to both test procedures, most inflation series are found to be I(0) at the 10 per cent significance level.

[10] It is assumed that the price level is I(1).

Judging by the t-statistics on $\hat{\alpha}$, there appears to be a large degree of heterogeneity in the data, as expected. For the rest of this paper, all inflation series are therefore considered as stationary.

For the output series, the ADF test is used, in addition to a modified version of the ADF test that allows for a polynomial deterministic trend function of order k, such as $x_t = a_0 t^0 + a_1 t^1 + ... + a_k t^k$, where $t = 1, 2, ..., T$. The selection of k is done using a general-to-specific strategy. In most cases, a k of 4 provides nice results both in terms of the unit-root test results and the business cycle approximation (see Figure 8). The appropriate critical values for a sample size of $T = 100$ are simply obtained by means of Monte Carlo simulations. Table 1 shows that the polynomial (Poly) test allows us to reject the null hypothesis at 10 per cent in all but one case; rejection is, however, possible at the 12 per cent level of significance. On the basis of this test, we can conclude that the output series are trend stationary, so we can therefore approximate potential output by means of a polynomial deterministic trend function.

3 A Brief Review of, and Some Issues with, Contemporal Aggregation

There exist various types of data aggregation, such as temporal, contemporal, or spatial, each creating potential sources of distortions and difficulties. Obviously, all types of aggregation may arise simultaneously, and this may lead to a complex combination of consequences that can significantly alter the inference or the forecasts an econometrician is attempting to make for a particular time series. In this study, our main concern pertains to the consequences of contemporal aggregation on parameter estimates and, as a result, on forecasting core inflation, although the effects of temporal aggregation could be of interest in this study, since we also analyze quarterly data that are temporally aggregated.

The problems associated with the aggregation of data, particularly contemporal aggregation, have received considerable attention in the literature. See, for example, Theil (1954), Grunfeld and Griliches (1960), Rose (1977), Sasaki (1978), Granger (1980, 1990), Tiao and Guttman (1980), Pesaran (2003), and Zaffaroni (2004). Other aspects of aggregation have also recently generated a large amount of research, namely in the field of temporal aggregation. For excellent surveys on, and recent developments in, temporal aggregation, see Howrey (1991) and Marcellino (1999); for spatial aggregation, see Anselin (1988) and Giacomini and Granger (2004).

By contemporal aggregation, the time series are simply constructed as

$$Y_t = \omega_1 y_{1,t} + ... + \omega_N y_{N,t}, \quad t = 1, ..., T \tag{3}$$

$$\omega_i \;>\; 0, \quad \sum_{i=1}^{N} \omega_i = 1, \tag{4}$$

where ω_i is the relative weights of the series $y_{i,t}$.[11] Then, Y_t is simply a linear transform of $y_{i,t}$ with a possibly non-identical spectrum. Virtually every macroeconomic time series of interest is generated using the same construction as in (3).

A time series such as the aggregate consumption measure from the national accounts, for instance, is the summation of individual consumption. When a consumption demand function is estimated using national accounts data, the outcome is then interpreted as the characterization of the so-called 'representative agent' (see Stoker 1993). But the results will not, in general, highlight the various spending behaviours that can be observed within a given population. If all the micro-units of a population behave exactly the same way and the underlying micro-relations are homogeneous (i.e., the micro-units respond in the same direction and in the same magnitude to the fluctuations of certain variables), then it will be appropriate to aggregate them. Granger (1987) also analyzes the effects of common factors across subaggregates and shows that their presence might play a dominant role in explaining the aggregate, even though they are not important at the micro level. Evidently, reality is such that economic units, whether it be individuals, firms, or industries, are quite heterogeneous in their behaviour, although a certain degree of generalization is, of course, possible.

Issues of contemporal aggregation can be divided into two components, modelling and forecasting, which can be viewed in terms of either static or dynamic models. Granger (1980) uses a spectral density approach to examine the consequences of aggregating dynamic equations and shows that, in cases as simple as AR(1) processes, different classes of models—different from the subaggregates—can be artificially generated by data aggregation. In particular, Granger shows that, by aggregating stationary AR(1) processes, long-memory or integrated processes can be generated. Similarly, Granger and Newbold (1977) show that summing two independent series that follow a stationary AR(1) process will result in a series that obeys an ARMA$(2,1)$. In general, the sum of N AR(1) will be an ARMA$(N, N-1)$ process, with the possibility, of course, that some of the ARMA roots cancel out.

Pesaran, Pierse, and Lee (1993) compare the persistence of shocks on aggregate output in the context of a multisectoral model. They find that they can obtain more precise estimates using disaggregate data rather than aggregate data, an empirical example that illustrates well the improvement that can be obtained in the estimates by conditioning on a larger

[11] This study ignores the potential effects that time-varying weights can have on inference or forecasting. These effects are discussed in van Garderen, Lee, and Pesaran (2000).

information set. Similar findings are reported by Tiao and Guttman (1980) for the case of forecasting moving-average processes, and by Lovell (1973) for the parameter estimates of a production function. Lütkepohl (1987) argues, and illustrates via analytical results and Monte Carlo simulations, that it is better to forecast some aggregate data of interest by means of forecasting disaggregated multiple time series if the DGP is known. Lütkepohl argues that if the DGP is unknown, then in finite samples it can be more appropriate to forecast the aggregate time series directly, because of model uncertainty and sampling variability. Similarly, Grunfeld and Griliches (1960) argue that the uncertainty regarding the true specification of the micro-relations can, in practice, favour aggregation by inflating the variance of the forecast error of the micro-relations. Granger (1990) also notes advantages of focusing on the aggregate rather than on the subaggregate data: (i) less time and effort is required to analyze and forecast a single time series than its components, and (ii) measurement errors are less likely to have an (significant) impact on the aggregate than on the subaggregate data.

Obviously, practitioners always face a notable degree of uncertainty regarding the DGP of the data they attempt to model and forecast. Given the aggregation issues noted above, it is difficult to judge beforehand whether one should invest time and efforts to forecast a time series from its components: one must carefully analyze the data before a sound decision can be made.

4 The General Specification

In this study, the models that are constructed rely on various assumptions for the data process that are made necessary by the many challenges of modelling and forecasting the time series at hand. Hence, we consider the following disaggregate model of inflation:

$$\begin{aligned} \pi_{i,t} &= \psi_i(L)X_{i,t} + \varepsilon_{i,t} \\ \varepsilon_{i,t} &\sim i.i.d.\,(0, \Lambda_{i,i}) \\ E\left[\varepsilon_{i,t}\varepsilon'_{i,t-s}\right] &= 0, \quad \forall\, t \neq s, \end{aligned} \tag{5}$$

where the innovations, $\varepsilon_{i,t}$'s, are vectors of random errors; $X_{i,t}$ is a matrix of explanatory variables with coefficient matrix, ψ_i; and the variance-covariance matrix, Λ, is diagonal. Although the assumption regarding the spherical structure of the disturbances is fairly strong, innovations are considered to be orthogonal, for simplicity. Of course, this assumption could be relaxed and the correlation structure across the disturbances could be exploited by estimating, say, a VAR, or by fully parameterizing an appropriate multivariate likelihood function as in Demers and Dupuis (2005), but we would then be faced with the curse of dimensionality.[12] Because this paper's main objective is to investigate the out-of-sample performance of the aforementioned methods, the empirical process of the $\varepsilon_{i,t}$'s is not of paramount importance.

As Lütkepohl (1987) and Clements and Hendry (1999) note, selecting the most appropriate model is crucial to obtaining accurate forecasts. Three lag selection criteria are considered: Akaike's (AIC), Schwartz's (SIC), and Hannan-Quinn's information criteria (HQIC). A maximum of $j = 11$ lags is permitted for the monthly frequency, and $j = 4$ for the quarterly frequency.

Parameter stability is another important aspect of model selection and testing for predictive ability, as argued by, among others, Clements and Hendry (1999) and Clark and McCracken (2003). It is possible that past observations of a certain information set, say X_t, Granger-cause (based on an in- or out-of-sample criteria) a variable, say Y_t, during a particular period of time, but that the causal relationship between Y_t and X_t has vanished because of a structural change, or vice versa. Hence, testing for forecast accuracy using an obsolete specification might be uninformative or, worse, misleading. Demers (2003) and Khalaf and Kichian (2003) argue that the Canadian Phillips curve exhibits significant non-linearities and that the assumption of structural stability is easily rejected by the data. In both Demers and Khalaf and Kichian's work, there is strong evidence that a structural change occurred in the early 1980s and again in the early 1990s, with the latter corresponding to the Bank of Canada's adoption of an official inflation target. Since our sample starts in January 1984, we can expect to find a break located around the 1990 period, and each equation of the system is therefore allowed to have a structural break (ARX-K models).

For simplicity, Andrews' (1993) test is applied to the null hypothesis that $\psi_t = \psi$ as opposed to the alternative hypothesis that $\psi_t \neq \psi$. Because dynamic models with distributed lags are used, a large set of specifications are possible; selecting one upon which to apply a stability test would amount, in this case, to estimating $3 \times j \times N \times (T - 2\lambda T)$ equations, λ being a trimming parameter set to 0.15.[13] Since our main aim in this study is to produce a forecasting device using minimal assumptions, a fixed specification with three lags for both the AR component and the exogenous variables is used to test for parameter stability, although we must acknowledge that this assumption could have an impact on both the timing

[12] Furthermore, this study does not analyze the effect of the potential cointegration within and across the micro-relationships. Nor does it examine the usefulness of sophisticated non-linear models, such as those considered by Demers (2003) or Khalaf and Kichian (2003). The only refinement that is employed here is the allowance for an unknown structural break.

[13] The number 3 is used because we compare the results from three information criteria.

and the significance of the structural break. Tests for multiple discrete breaks such as those suggested by Bai and Perron (1998) are not implemented, but of course it would be possible to find that some micro-relations have undergone more than one shift over time. It is also possible that the breaks are stochastic and continuous, as suggested by the empirical results obtained by Khalaf and Kichian, so that models with time-varying parameters would be most appropriate for forecasting. These issues, however, are beyond the scope of this paper, and the possible structural changes are approximated as a one-time shift of the vector of population parameters.

5 Empirical Results

Our benchmark model is a standard aggregated Phillips curve (see, e.g., Fillion and Léonard 1997; Demers 2003):

$$\pi_t = \psi(L)X_t + \varepsilon_t, \tag{6}$$

where the matrix X_t includes lags of core inflation, lags of the real exchange rate growth, and lags of the output gap. Obviously, other key variables (e.g., commodity prices, money aggregates, employment) could be tested for their forecasting usefulness; this is not done because of time and space constraints. Furthermore, the current information set represents a solid benchmark. For the second model, we allow for a complete structural break in the relationship, yielding:

$$\pi_t = \psi^m(L)X_t^m + \varepsilon_t^m, \qquad m = 1, 2. \tag{7}$$

The same type of specification is used to estimate models for the disaggregated data, both monthly and quarterly.

Because of space constraints, only a few selected parameter estimates are studied. Hence, the results based on the more liberal criteria, AIC, are compared with the results from a more conservative criteria, SIC, while we report only the results based on the QPM output-gap measure.[14] The results of these specifications are shown in Tables 2 to 9. All parameter estimates are reported as sums over the lags; p-values are shown in parentheses. Selected lags are reported in column 2 of the tables.

Before discussing the results in more detail, one finding is worth highlighting. After careful analysis, we have found that the inflation series for Electricity is by far the most difficult series to work with. This could be largely explained by regulatory changes that occurred in Ontario during the 2002–03 period, and because of rebates offered to customers

[14] The results from HQIC and the two alternative output-gap measures tend to be similar to those described herein. They are not reported, but they are available from the first author upon request.

in Alberta during the same period. As Figure 1 shows, the behaviour of the series during this period is dramatically different. Because these events happened in the very last part of the sample, it is difficult to correctly model that particular series, even for a structural change model. Hence, data from the complete sample are used to estimate the parameters and no structural-break test is performed on the Electricity ARX equation, nor is it allowed into the micro-relation.

Because the specifications we evaluate are somewhat restricted, and individual price indexes could most certainly be better modelled by very different factors that are omitted from this study, conclusions about sectors are not easily drawn from the empirical results described below. As already noted, we do not attempt to find the best individual specifications, but the best technique and aggregation level with which to forecast aggregate inflation, although our approach relies in part on the Phillips curve theory.

5.1 Monthly data

5.1.1 Quality of adjustment

As one might expect, the quality of adjustment (i.e., the R^2) varies greatly across the components, and is largely affected by the degree of persistence present in the inflation series. In most cases, the R^2 is less than 0.25 and, according to the $\sup F(T_B)$ statistics, there is strong evidence that each relationship has undergone a structural change at some point. It is also worth noting that, for a majority of specifications, the timing of the break tends to be within the same period (that is, near the early nineties), a result also found in other studies that use aggregate quarterly Canadian data (see Demers 2003; Khalaf and Kichian 2003). This period coincides with the adoption of an official inflation target by the Bank of Canada in 1991. We have no solid explanation to provide for the specifications that experience a break during the second half of the nineties.

Other than the stability test, no diagnostic tests are performed on the residuals, since (out-of-sample) forecasting is our primary concern, not in-sample statistical inference. To compare some of the empirical findings, we use as reference the results obtained from the AIC and the QPM output-gap measure.[15]

5.1.2 Inflation persistence

Tables 2 to 5 show that monthly inflation persistence, approximated by the sum of the AR parameters and denoted as $\sum AR$, exhibits a substantial degree of heterogeneity across

[15]In this study, AIC tends to favour a higher degree of persistence, compared with SIC.

components, ranging from strong negative serial correlation to strong positive, and that it is very sensitive to the stability hypothesis. For core inflation, the measured persistence goes from about 0.75 in the case where we believe the Canadian Phillips curve is stable, to roughly 0 if this assumption is relaxed. Some inflation components, however, such as Rent or Depreciation, remain fairly persistent, even after allowing for a complete shift in the population parameters. Automobile Insurance is the only component to exhibit an increase in persistence when we account for a structural change in the parameters.

Based on the lag selection by the AIC and the QPM output gap, the calculated weighted persistence is compared with that obtained by the estimates from the aggregate measure.[16] When no break is permitted (Tables 2 and 4), and using either level of disaggregation, the weighted measure of persistence is about 0.25, compared with 0.75 when it is estimated directly from the aggregate data. Interestingly, when we allow for at least one structural break (Tables 3 and 5), all the estimated measures of persistence fall virtually to zero.[17] Using U.S. data, similar results are obtained by Clark (2003), who shows that aggregation does not cause the inflation persistence to be high; he argues instead that the estimated high persistence is due to the presence of a structural break in the inflation series.

5.1.3 Output-gap response

The response to the output gap, denoted as $\sum gap$, varies widely across the components and depends on how the output gap is measured, based on the assumption that the Phillips curve relations are stable over time, and, to a lesser extent, on the lag selection criteria from the QPM measure. Parameter estimates are, in general, supportive of the hypothesis that the response of inflation to output-gap shocks has diminished somewhere near the period of the early nineties, with almost half of the parameter estimates being insignificant after the structural break occurred in the relation.

Using AIC as the lag selection criteria, and using the QPM output-gap measure (Tables 2 and 4), the calculated weighted aggregate output-gap response is about 0.009 when the first level of disaggregation is used, compared with about 0.014 for the second level, which is the same as when it is directly estimated from core inflation. When we allow for a break (Tables 3 and 5), the first level of aggregation suggests a weighted coefficient of about 0.003, whereas the second level suggests a much larger coefficient of 0.020, compared with about 0.005 when it is estimated directly from core inflation.

[16] The weights used are from the most recent CPI basket.

[17] The large negative AR component associated with the Electricity inflation series has only a small impact, due to its low weight of 2.65 per cent.

5.1.4 Exchange-rate response

The response to changes in the real Canada-U.S. exchange rate, denoted as $\sum exc$, is also very different across components. For some sectors where external exposure and imports are important, such as food-related items, some goods, and traveller accommodations (Hotel), the estimated response to exchange rate growth is strongly significant and the coefficients are of the expected sign (i.e., negative). As Leung (2004) finds, there is no evidence of real exchange rate pass-through for a large majority of components.

As before, using the AIC and the QPM output-gap measure (Tables 2 and 4), the first level of disaggregation shows a coefficient on the exchange rate of 0.002, compared with -0.011 for the second level of disaggregation and -0.031 for core inflation. The odd results for the first level can be explained by the large positive and significant exchange rate coefficient in the Semi-Durable equation. By setting it to zero, the weighted sum falls to -0.007. After allowing for a shift in parameters, the weighted estimates are -0.013 and -0.017 for the first and second level of disaggregation, respectively. These estimates suggest a much lower degree of pass-through than the aggregate estimate of -0.021, which, although significant, is well below the estimate suggested when no structural break is accounted for. This last result is commonly found in other studies where the coefficient on the real exchange rate is no longer significant once a shift in parameters is accounted for.[18] This conclusion is robust to either of the output-gap measures used.

5.2 Quarterly data

5.2.1 Quality of adjustment

Compared with monthly data, quarterly data provide, in general, a far better quality of adjustment, for both the micro-relations and core inflation, although some components, such as Communication and Hotel, remain difficult to explain using simple reduced-form models. When a structural break is accounted for, the fit for the model of core inflation vanishes almost entirely, whereas there is no systematic effect on the quality of adjustment for the components: some micro-relations benefit, while others suffer. As for the monthly data, evidence of a structural change is strong for almost every single component. Overall, disaggregate data provide a better fit than the aggregated models.

[18] See, e.g., Leung (2004), Demers (2003), and Khalaf and Kichian (2003).

5.2.2 Persistence, output-gap, and exchange rate responses

Similar to the results based on monthly data, inflation persistence falls substantially for most components when a break is accounted for, while the drop for core inflation is quite dramatic, falling from about 0.8 to virtually zero (Tables 6 and 7).

For the output-gap response, the choice of the output-gap measure plays, again, an important role in determining whether aggregate-demand conditions have an impact on the growth of the various core consumer price indexes. As Leung (2004) reports, Food items appear to be the most sensitive to output-gap variations, while they also exhibit significant exchange rate sensitivity. This conclusion remains true even after allowing for a structural change in the relationship. Hotel prices show a high coefficient on the exchange rate variable, although the parameters are not always precisely estimated, judging by their associated p-values (Table 8 and 9).

6 Comparison of Out-of-Sample Forecasts

Among the various models that are compared, we have, as a base case, the random-walk (i.e., the no-change) model:

$$\pi_{i,t} = \pi_{i,t-1} + \varepsilon_{i,t}, \tag{8}$$

and the AR(p) model:

$$\pi_{i,t} = \phi_i(L)\pi_{i,t-1} + \varepsilon_{i,t}. \tag{9}$$

From the aggregate and disaggregate models, the (iterated) forecasts obtained by (6) and (7) are also compared to determine whether the allowance for a structural change can improve the out-of-sample forecasts. It should be noted also that we do not compare the forecast performance of the direct forecasting method against the iterated method (see, e.g., Marcellino, Stock, and Watson 2004).

Because it is now well recognized that a combination of individual forecasts tends to improve the forecast accuracy over individual forecasts, forecasts are combined from each subaggregate model and compared with the combined aggregate forecasts. To combine the forecasts, a simple arithmetic mean is used; more sophisticated approaches are left for future research.[19]

To build the aggregate forecasts, we use the weighted forecasts of each subaggregate using a given technique, rather than select the best technique for each given index, which would

[19] For a review of forecast combination methods, see Granger and Ramanathan (1984), and Li and Tkacz (2004).

tend to favour even more the use of disaggregate data over aggregate data. Our approach closely follows that of Hubrich (2005).

6.1 Testing for equality of forecast accuracy

To test for the hypothesis that the h-step-ahead forecasts from two non-nested competing models are equal, the test proposed by Diebold and Mariano (1995, DM) is used. From two competing models, A and B, and denoting the vector of forecast errors as $\{e_t\}_{t=1}^{n}$ (n being the number of out-of-sample forecast errors), and the loss differential of interest as $L_t(e_t)$, the MSFE loss differential is defined as $L_t(e_t) = e_{At}^2 - e_{Bt}^2$. Then, the null hypothesis that the forecasts from models A and B are equivalent, in the mean squared error, can be tested using the following test statistics:

$$S = \frac{\bar{L}_t}{\sqrt{\hat{V}\left(\bar{L}_t\right)}}, \tag{10}$$

where $\bar{L}_t$ is simply the average loss differential of interest and $\hat{V}\left(\bar{L}_t\right)$ is an estimate of the asymptotic variance of $\bar{L}_t$. Among the various robust methods that are available in the literature to estimate $\hat{V}$, we use the quadratic spectral kernel proposed by Andrews (1991) with the bandwidth set to $h-1$. To account for the small sample bias of the test statistic and the possibility of fat-tailed forecast errors, we discuss the results from the DM test using the correction proposed by Harvey, Leybourne, and Newbold (1997). Under the null hypothesis, the modified version of the S-statistics is asymptotically distributed as a student-t distribution with $n-1$ degrees of freedom.

It is also possible that two econometric models may capture the various features of the data with varying degrees of accuracy, depending on the criteria. Such features could be related to rare events that translate into large and unusual changes in the rate of inflation, for which the available information set cannot provide an explanation. These resulting *large* forecast errors will then be located in the tails of the empirical distribution of the forecast errors, as signalled by the excess kurtosis found in the various vectors of forecast errors considered in this study.

To test for equality of forecast accuracy when such features are present in the data, van Dijk and Franses (2003) propose a weighted version of the DM test that allows for discrimination in the data. In effect, their approach posits that certain areas of the empirical distribution are given less weight than others. They also suggest three convenient data-dependent weight functions, ω_t:

$$
\begin{aligned}
\omega_T(\omega_t) &= 1 - \xi(\pi_t)/\max\left(\xi(\pi_t)\right), \\
\omega_{LT}(\omega_t) &= 1 - \Gamma(\pi_t), \text{ and} \\
\omega_{RT}(\omega_t) &= \Gamma(\pi_t),
\end{aligned}
$$

where $\xi(\pi_t)$ is the density function of inflation, such that ω_T puts more weight on the tail events; $1 - \Gamma(\pi_t)$ is a cumulative distribution function, which assigns more weight to observations located on the left-hand side of the distribution; and $\Gamma(\pi_t)$ focuses only on data located on the right-hand side of the distribution. By using such a variant of the DM test, we can test whether a particular forecasting strategy is better than an alternative method when we focus only on a specific region of the distribution of the forecast errors.

The theoretical and finite-sample properties of the various testing strategies are discussed in detail by Clark (1999), Harvey, Leybourne, and Newbold (1999), and van Dijk and Franses (2003).

6.2 Test results

6.2.1 Monthly data

As Table 10 shows, the best overall model for the one-month-ahead forecast is obtained using the first level of disaggregation (i.e., six components) for the Phillips curve model with a break, using the sectoral output-gap measure and based on the lag selection by SIC. This model is very closely followed, however, by a similar model that uses the second level of disaggregation and the QPM output-gap measure. Compared with the best model from the aggregate data, the best overall model reduces the RMSFE by about 9 per cent and, according to the DM test, is significantly better than the aggregate forecast with a p-value of 7 per cent. While the two competing forecasts are slightly different, judging by the RMSFE statistics, each model is subject to almost the same pattern of forecast errors (see Figure 9). The fact that the out-of-sample forecast errors are very similar across the two models suggests that they each convey essentially the same information about future inflation. Harvey, Leybourne, and Newbold (1998), however, also show that the power of the DM test can be quite low when the competing forecasts are correlated, as we have done in our study.

For the two-month-ahead forecasts, the best overall forecasts are obtained from the combined disaggregated models based on the QPM output-gap measure and lags selected by SIC. For the aggregate data, the best forecasts are provided by the Phillips curve with a break and lag selection by SIC. The p-value that these two models provide statistically equal forecasts is 0.11.

For the twelve-month-ahead forecasts, the best forecasts are provided by the disaggregated model with a break and using the sectoral output-gap measure, and the lag selection is again done by SIC. For the aggregate data, various models provide comparable RMSFEs, but the best model is achieved using the total output-gap measure and lags selected by AIC. The p-value that these two competing models are statistically equal is only 0.17.

6.2.2 Quarterly data

From the quarterly data (Table 11), the best overall model for the one-quarter-ahead forecast is provided by the Phillips curve based on the second level of disaggregation with a break, using the total output-gap measure and the lag selection by SIC. In the case of aggregate data, the best forecasts are given by the combination of all forecasts when the QPM output gap is used. In this case, AIC and SIC suggest identical lag structures. According to these two models, the use of disaggregate data instead of aggregate data reduces the RMSFE by about 15 per cent, although, as in the case of some monthly models, the pattern of forecast errors is very similar. From the DM test, the best disaggregated model yields statistically better forecasts with a p-value of 0.06.

For the four-step-ahead forecasts, the RMSFEs from the best aggregate and disaggregate models seem almost identical (not shown). This result is confirmed by the DM test (p-value: 0.49).

6.2.3 One-quarter-ahead forecast: monthly versus quarterly data

An important question remains: to forecast the one-quarter-ahead rate of core inflation, should we use monthly data, which represent a richer set of information, or simply quarterly data? By comparing the best overall one-quarter-ahead forecasts from each frequency, we note a reduction in the RMSFE of about 9 per cent, but, according to the DM test, the p-value that the two competing forecasts are equivalent is only 0.32, which strongly suggests that they are indeed equivalent. The best disaggregate forecasts are only slightly better, with a p-value of 0.10. Although statistical support for disaggregate quarterly models is rather limited, disaggregation can still be very useful: we could improve the one-quarter-ahead forecast, since CPI data are released every month.

In each situation noted above, using the weighted DM test proposed by van Dijk and Franses deteriorates the p-values of rejecting the null hypothesis. This leads us to conclude that the estimation of micro-relations does not, in general, better capture tail events in the inflation process. This result implies that tail events, which could be associated with non-linearities, cannot be uncovered by linear micro-relations. Perhaps more sophisticated and flexible non-linear specifications for the micro-relations could yield significant improvement on this front. These specifications should capture short-lived episodes of all kinds. In particular, some monthly series exhibit a high degree of volatility, so that volatility models such as the GARCH class or regime-switching class of models could be useful in modelling the micro-relations. In other words, the models should be able to capture conjectural changes instead of structural changes, as was done in our study.

7 Conclusion

In this paper, we have compared models of Canadian core inflation by direct modelling of the aggregate measure and by indirect modelling of the subaggregates from two levels of disaggregation (6 and 19). We have emphasized the usefulness of using monthly and quarterly disaggregate models of inflation to forecast core inflation in Canada. By testing these various approaches at modelling core inflation, it appears that the forecasting accuracy can be improved by using disaggregated models of monthly core inflation, most notably for short-horizon forecasts. At the disaggregated level, Phillips curve types of models appear to contain valuable information about future inflation, as theory predicts and as found by Hubrich (2005).

Meanwhile, the gains from using monthly disaggregate data to forecast the quarterly rate of core inflation are quite moderate and statistically insignificant according to tests for equality of forecast accuracy, although the RMSFEs can be reduced by nearly 10 per cent. For the purpose of forecasting, the relative cost of using such a large set of information appears to provide moderate value-added and the use of aggregate quarterly data seems to provide core inflation forecasts that are at least as accurate as those obtained by modelling various micro-relations. Although the variability of core inflation has been relatively low since the introduction of the Bank of Canada's inflation target, predicting core inflation during the target period remains a challenging task. Because the technology to obtain quarterly forecasts from monthly disaggregate data is readily available to Bank staff, it will be interesting to see how this forecasting strategy evolves over time as more data become available. Of course, by selecting the best forecasting model for each price index of interest, instead of using a particular technique, we could expect the payoff of disaggregation to be even larger. This would be an interesting practical extension of this paper in searching for the best aggregate forecast possible.

The fact that the RMSFE's are reduced—sometimes by a large amount—when micro-relations are estimated is nevertheless an interesting empirical result, which supports the usefulness of forecasting inflation by means of disaggregated models. In light of the recent work by Clark and West (2004, 2005) on testing for equality of forecast accuracy, the reduction of the RMSFEs, even when so many parameters are estimated, leads us to conclude that disaggregate models are a useful alternative.

As reported in many previous studies on inflation, inflation persistence appears to be an artifact, most likely resulting from shifts in the mean and not from aggregation of the data. As for the response of core inflation to shocks from the output gap and real exchange rate, elasticity estimates are also quite sensitive to the assumption of parameter stability, although it is important to recall that the main purpose of this paper is not to explicitly attempt to find the most appropriate specification for each of the estimated micro-relations, but to find the best forecasting strategy under simplistic assumptions. Assuming that the Phillips curve parameters might have changed over time, whether in the macro- or the micro-relations, the estimated coefficients are generally lower during the second period of the sample.

A natural extension of this work would be to investigate spatial aggregation; i.e., whether it is more appropriate to forecast regional indexes or the aggregate, as has been done in the euro area. For future research, it would also be interesting to compare density forecasts suggested by the macro- and micro-relations. Another extension would be to merge various monthly and quarterly forecasts together, to determine whether quarterly inflation forecasts can be improved, as suggested by Corrado and Greene (1988) and Howrey, Hymans, and Donihue (1991).

References

Andrews, D.W.K. 1991. "Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica* 59**:** 1465–71.

__________. 1993 "Tests for Parameter Instability and Structural Change with Unknown Change Point." *Econometrica* 61**:** 821–56.

Anselin, L. 1988. *Spatial Econometrics: Methods and Models*. Doerdrecht: Kluwer Academic Publishers.

Bai, J. and P. Perron. 1998. "Estimating and Testing Linear Models with Multiple Structural Changes." *Econometrica* 66: 47–78.

Balke, N.S. and M.A. Wynne. 2003. "The Relative Price Effects of Monetary Shocks." Federal Reserve Bank of Dallas Working Paper No. 0306.

Benalal, N., J.-L. del Hoyo, B. Landau, M. Roma, and F. Skudelny. 2004. "To Aggregate or Not to Aggregate? Euro Area Inflation Forecasting." European Central Bank Working Paper No. 374.

Blis, M., P.J. Klenow, and O. Kryvtsov. 2003. "Sticky Prices and Monetary Policy Shocks." *Federal Reserve Bank of Minneapolis Quarterly Review* 27: 2–9.

Butler, L. 1996. *A Semi-Structural Method to Estimate Potential Output: Combining Economic Theory with a Time-Series Filter*. Technical Report No. 77. Ottawa: Bank of Canada.

Cayen, J.–P. and S. van Norden. 2002. "La fiabilité des estimations des écarts de production au Canada." Bank of Canada Working Paper No. 2002–10.

Chacra, M. 2002. "Oil-Price Shocks and Retail Energy Prices in Canada." Bank of Canada Working Paper No. 2002–38.

Chen, S.-S. and C. Engle. 2004. "Does 'Aggregation Bias' Explain the PPP Puzzle?" NBER Working Paper No. 10304.

Clark, T.E. 1999. "Finite-Sample Properties of Tests for Equal Forecast Accuracy." *Journal of Forecasting* 18: 489–504.

Clark, T.E. 2003. "Disaggregate Evidence on the Persistence of Consumer Price Inflation." Federal Reserve Bank of Kansas City, RWP 03–11.

Clark, T.E. and M.W. McCracken. 2003. "The Power of Tests of Predictive Ability in the Presence of Structural Breaks." University of Missouri–Columbia, Unpublished manuscript.

Clark, T.E. and K.D. West. 2004. "Using Out-of-Sample Mean Squared Prediction Errors to Test the Martingale Difference Hypothesis." University of Wisconsin, Unpublished manuscript.

__________. 2005. "Approximately Normal Tests for Equal Predictive Accuracy in Nested Models." University of Wisconsin, Unpublished manuscript.

Clements, M.P. and D.F. Hendry. 1999. *Forecasting Non-Stationary Time Series.* Cambridge, Mass.: MIT Press.

Corrado, C. and M. Greene. 1988. "Reducing Uncertainty in Short-Term Projections: Linkage of Monthly and Quarterly Models." *Journal of Forecasting* 7: 77–102.

Demers, F. 2003. "The Canadian Phillips Curve and Regime Shifting." Bank of Canada Working Paper No. 2003–32.

Demers, F. and D. Dupuis. 2005. "Forecasting Canadian GDP: Region-specific versus Countrywide Information." Bank of Canada Working Paper No. 2005–31.

Dickey, D.A. and W.A. Fuller. 1979. "Distribution of the Estimator for Autoregressive Time Series with a Unit Root." *Journal of the American Statistical Association* 74: 427–31.

Diebold, F.X. and R.S. Mariano. 1995. "Comparing Predictive Accuracy." *Journal of Business and Economic Statistics* 13: 253–63.

Fillion, J.-F. and A. Léonard. 1997. "La courbe de Phillips au Canada: un examen de quelques hypothèses." Bank of Canada Working Paper No. 97-3.

Franses, P.H. and R. Paap. 2003. *Periodic Time Series Models.* Oxford: Oxford University Press.

Giacomini, R. and C.W.J. Granger. 2004. "Aggregation of Space–Time Processes." *Journal of Econometrics* 118: 7–26.

Granger, C.W.J. 1980. "Long Memory Relationships and the Aggregation of Dynamic Models." *Journal of Econometrics* 14: 227–38.

__________. 1987. "Implications of Aggregation with Common Factors." *Econometric Theory* 3: 208–22.

__________. 1990. "Aggregation of Time Series Variables – A Survey." In *Disaggregation in Econometric Modelling*, edited by T. Barker and H. Pesaran, London: Routledge.

Granger, C.W.J. and P. Newbold. 1977. *Forecasting Economic Time Series*. New York: Academic Press.

Granger, C.W.J. and R. Ramanathan. 1984. "Improved Methods of Combining Forecasts." *Journal of Forecasting* 3: 197–204.

Gregory, A.W. and J.J. Reeves. 2001. "Estimation and Inference in ARCH Models in the Presence of Outliers." Queen's University, Unpublished manuscript.

Grunfeld, Y. and Z. Griliches. 1960. "Is Aggregation Necessarily Bad?" *Review of Economics and Statistics* 42: 1–13.

Harvey, D.I., S.J. Leybourne, and P. Newbold. 1997. "Testing the Equality of Prediction Mean Squared Error." *International Journal of Forecasting* 13: 281–91.

__________. 1998. "Test for Forecast Encompassing." *Journal of Business and Economic Statistics* 16: 254–59.

__________. 1999. "Forecast Evaluation Tests in the Presence of ARCH." *Journal of Forecasting* 18: 435–45.

Howrey, E.P. 1991. "New Methods for Using Monthly Data to Improve Forecast Accuracy." In *Comparative Performance of U.S. Econometric Models*, edited by L.R. Klein. New York: Oxford University Press.

Howrey, E.P., S.H. Hymans, and M.R. Donihue. 1991. "Merging Monthly and Quarterly Forecasts: Experience with MQEM." *Journal of Forecasting* 10: 225–68.

Hubrich, K. 2005. "Forecasting EURO Area Inflation: Does Aggregating Forecasts by HICP Component Improve Forecast Accuracy?" *International Journal of Forecasting* 21: 119–36.

Jondeau, E., H. Le Bihan, and F. Sédillot. 1999. "Modélisation et prévisions des indexes de prix sectoriels." Banque de France NER 68.

Khalaf, L. and M. Kichian. 2003. "Exact Testing of the Phillips Curve." Bank of Canada Working Paper No. 2003–7.

Kichian, M. 2001. "On the Nature and the Stability of the Canadian Phillips Curve." Bank of Canada Working Paper No. 2001–4.

Leung, D. 2004. "An Empirical Analysis of Exchange Rate Pass Through into Consumer Prices." Bank of Canada, RM–03–005.

Li, F. and G. Tkacz. 2004. "Evaluating Linear and Non-Linear Time-Varying Forecast-Combination Methods." *Studies in Nonlinear Dynamics & Econometrics* 8: article 2.

Lovell, C.A.K. 1973. "A Note on Aggregation Bias and Loss." *Journal of Econometrics* 1: 301–11.

Lütkepohl, H. 1987. "Forecasting Contemporaneously Aggregated Vector ARMA Processes." *Journal of Business and Economics Statistics* 2: 201–14.

Macklem, T. 2001. "A New Measure of Core Inflation." *Bank of Canada Review* (Autumn): 3–12.

Marcellino, M. 1999. "Some Consequences of Temporal Aggregation." *Journal of Business and Economic Statistics* 17: 129–36.

Marcellino, M., J.H. Stock, and M.W. Watson. 2003. "Macroeconomic Forecasting in the Euro Area: Country Specific versus Area-Wide Information." *European Economic Review* 47: 1–18.

__________. 2004. "A Comparison of Direct and Iterated Multistep AR Methods for Forecasting Macroeconomic Time Series." Harvard University, Unpublished manuscript.

Pagan, A. 1984. "Econometric Issues in the Analysis of Regressions with Generated Regressors." *International Economic Review* 25: 221–46.

Perron, P. 1991. "Test Consistency with Varying Sampling Frequency." *Econometric Theory* 7: 341–68.

———. 1997. "Further Evidence on Breaking Trend Functions in Macroeconomic Variables." *Journal of Econometrics* 80: 355–85.

Perron, P. and G. Rodríguez. 2003. "Searching for Additive Outliers in Nonstationary Time Series." *Journal of Time Series Analysis* 24: 193–220.

Pesaran, M.H. 2003. "Aggregation of Linear Dynamic Models: An Application to Life-Cycle Consumption Models Under Habit Formation." *Economic Modelling* 20: 383–415.

Pesaran, M.H., R.G. Pierse, and K.C. Lee. 1993. "Persistence, Cointegration, and Aggregation." *Journal of Econometrics* 56: 57–88.

Rose, D.E. 1977. "Forecasting Aggregates of Independent ARIMA Processes." *Journal of Econometrics* 5: 323–45.

Sasaki, K. 1978. "An Empirical Analysis of Linear Aggregation Problems: The Case of Investment Behavior in Japanese Firms." *Journal of Econometrics* 7: 313–31.

Stoker, T.M. 1993. "Empirical Approaches to the Problem of Aggregation Over Individuals." *Journal of Economic Literature* 31: 1827–74.

Theil, H. 1954. *Linear Aggregation of Economic Relations*. Amsterdam: North Holland.

Tiao, G.C. and I. Guttman. 1980. "Forecasting Contemporal Aggregates of Multiple Time Series." *Journal of Econometrics* 12: 219–30.

van Dijk, D. and P.H. Franses. 2003. "Selecting a Nonlinear Time Series Model Using Weighted Tests of Equal Forecast Accuracy." Econometric Institute Report No. EI 2003–10.

van Garderen, K.J., K. Lee, and M.H. Pesaran. 2000. "Cross-Sectional Aggregation of Non-Linear Models." *Journal of Econometrics* 95: 285–331.

Zaffaroni, P. 2004. "Contemporaneous Aggregation of Linear Dynamic Models in Large Economies." *Journal of Econometrics* 120: 75–102.

Zellner, A. and J. Tobias. 2000. "A Note on Aggregation, Disaggregation and Forecasting Performance." *Journal of Forecasting* 19: 457–69.

Table 1: Unit-Root Test Results

	Monthly		Quarterly	
Component／Test	ADF	P97*	ADF	P97*
Durable	−5.42	−14.83	−6.47	−7.13
Semi-Durable	−17.72	−18.33	−7.71	−14.19
Non-Durable-X	−5.63	−20.48	−2.61	−6.98
Food-X	−5.91	−15.93	−4.79	−9.32
Electricity	−5.81	−10.82	−3.47	−4.69
Services-X	−16.00	−20.26	−7.57	−11.12
Shelter-X	−2.37	−6.96	−1.57	−6.43
Other Food	−8.89	−14.98	−2.55	−6.73
Food away from Home	−15.12	−22.13	−7.58	−27.49
Services-XFT	−6.11	−17.84	−7.00	−8.50
Automobile Insurance	−3.80	−5.53	−4.33	−6.96
Communication	−7.25	−4.36	−8.52	−9.23
Local Transportation	−15.98	−17.33	−3.63	−4.59
Alcohol in Restaurants	−9.15	−20.53	−2.13	−8.75
Hotel	−6.54	−20.43	−1.22	−8.92
Rent	−2.34	−4.37	−1.52	−3.07
Property Tax	−15.98	−20.75	−4.53	−10.96
Depreciation	−2.91	−6.00	−2.25	−6.23
Repairs and Other Shelter Items	−7.27	−21.67	−1.91	−7.98
Home Insurance	−4.09	−12.19	−4.01	−5.89
Durable Ex. Automobiles	−4.76	−16.67	−2.48	−6.17
Automobiles	−14.32	−15.18	−2.65	−7.19
Semi-Durable	−17.72	−18.33	−7.71	−14.19
Alcohol	−5.49	−16.05	−1.95	−7.59
Other Non-Dur.	−5.67	−8.09	−3.19	−6.47
Core CPI	−4.29	−16.14	−2.98	−8.07

*Test includes only a level shift.

(*continued*)

Table 1 (*concluded*)

	Monthly		Quarterly	
Component／Test	ADF	Poly	ADF	Poly
Durable Manufacturing Goods	-4.61	-4.69	-4.75	-4.19
Non-Durable Manufacturing Goods	-3.18	-3.66	-2.80	-4.48
Business Goods Output	-5.17	-5.13	-5.64	-6.08
Business Services Output	-4.15	-4.72	-4.32	-5.26

Lags are selected by the t-sig rule.

ADF test 10 per cent critical value (T=100): -2.58.

P97 test 10 per cent critical value (T=100): -4.58.

Polynomial test (order 4) 10 per cent critical value (T=100): -4.29.

Table 2: Monthly Data – Results Using the QPM Output-Gap Measure*

Component	Lag**	$\sum AR$	$\sum gap$	$\sum exc$	R^2	$\sup F(T_B)$	T_B	σ_u
Durable	$(1,1,1)$	0.150 (0.03)	0.009 (0.59)	-0.040 (0.22)	0.031	45.67	90:03	0.384
	$(6,6,1)$	0.452 (0.01)	-0.005 (0.02)	-0.023 (0.48)	0.153			0.368
Semi-Durable	$(1,1,1)$	-0.243 (0.00)	0.013 (0.47)	0.037 (0.32)	0.063	39.43	92:05	0.427
	$(5,1,9)$	0.253 (0.00)	-0.003 (0.88)	0.135 (0.00)	0.215			0.340
Non-Durable-X	$(3,1,1)$	0.462 (0.00)	0.022 (0.05)	0.006 (0.78)	0.154	49.77	91:02	0.253
	$(8,1,1)$	0.654 (0.00)	0.022 (0.05)	-0.002 (0.93)	0.202			0.249
Food-X	$(1,2,1)$	0.013 (0.86)	0.052 (0.00)	-0.018 (0.39)	0.142	36.46	91:07	0.243
	$(1,2,1)$	0.013 (0.86)	0.052 (0.00)	-0.018 (0.39)	0.142			0.243
Electricity	$(3,1,1)$	-1.278 (0.00)	-0.067 (0.43)	-0.027 (0.88)	0.286	–	–	1.957
	$(5,1,2)$	-1.829 (0.00)	-0.096 (0.25)	0.013 (0.31)	0.323			1.911
Services-X	$(1,1,1)$	0.021 (0.76)	0.020 (0.10)	-0.012 (0.62)	0.018	35.92	88:10	0.282
	$(1,5,1)$	0.013 (0.85)	0.015 (0.05)	0.010 (0.69)	0.054			0.279
Shelter-X	$(3,1,1)$	0.729 (0.00)	0.006 (0.41)	-0.014 (0.37)	0.339	41.33	90:05	0.177
	$(7,1,1)$	0.853 (0.00)	0.004 (0.56)	-0.022 (0.17)	0.379			0.173
Core CPI	$(4,1,1)$	0.600 (0.00)	0.014 (0.05)	-0.028 (0.04)	0.190	49.91	91:10	0.151
	$(9,1,1)$	0.761 (0.13)	0.014 (0.03)	-0.031 (0.02)	0.250			0.147

*Joint test of significance p–value in parenthesis. Estimates of the constant are not reported.

**The first row refers to the lag selection by SIC; second row refers to AIC.

Table 3: Monthly Data – Results Using the QPM Output-Gap Measure With Break*

Component	Lag**	$\sum AR$	$\sum gap$	$\sum exc$	R^2	Sample starts	σ_u
Durable	$(1,1,1)$	0.052 (0.49)	−0.022 (0.17)	−0.047 (0.12)	0.037	90:04	0.330
	$(1,4,1)$	0.019 (0.79)	−0.029 (0.02)	−0.045 (0.13)	0.094		0.322
Semi-Durable	$(1,1,1)$	−0.341 (0.00)	−0.008 (0.75)	−0.018 (0.67)	0.119	92:06	0.439
	$(1,1,8)$	−0.352 (0.00)	−0.007 (0.71)	−0.025 (0.00)	0.253		0.415
Non-Durable-X	$(1,1,1)$	0.070 (0.37)	0.006 (0.62)	−0.007 (0.75)	0.007	91:03	0.239
	$(1,4,1)$	0.001 (0.98)	0.014 (0.04)	−0.015 (0.49)	0.068		0.235
Food-X	$(1,1,1)$	0.034 (0.67)	0.038 (0.00)	−0.014 (0.45)	0.087	91:08	0.203
	$(1,2,2)$	−0.011 (0.98)	0.045 (0.00)	−0.031 (0.08)	0.123		0.200
Electricity	$(3,1,1)$	−1.278 (0.00)	−0.067 (0.43)	−0.027 (0.88)	0.286	–	1.957
	$(5,1,2)$	−1.829 (0.00)	−0.096 (0.25)	0.013 (0.31)	0.323		1.911
Services-X	$(1,1,1)$	0.090 (0.21)	0.014 (0.25)	0.005 (0.85)	0.019	88:11	0.265
	$(1,1,1)$	0.090 (0.21)	0.014 (0.25)	0.005 (0.85)	0.019		0.265
Shelter-X	$(3,1,1)$	0.451 (0.00)	−0.003 (0.88)	−0.009 (0.56)	0.106	90:06	0.168
	$(3,1,1)$	0.451 (0.00)	−0.003 (0.88)	−0.009 (0.56)	0.106		0.168
Core CPI	$(1,1,1)$	−0.088 (0.26)	0.005 (0.46)	−0.021 (0.12)	0.024	91:11	0.146
	$(1,1,1)$	−0.088 (0.26)	0.005 (0.46)	−0.021 (0.12)	0.024		0.146

*Joint test of significance p–value in parenthesis. Estimates of the constant are not reported.

**The first row refers to the lag selection by SIC; second row refers to AIC.

Table 4: Monthly Data – Results Using the QPM Output-Gap Measure*

Component	Lag**	$\sum AR$	$\sum gap$	$\sum exc$	R^2	sup $F(T_B)$	T_B	σ_u
Other Food	$(1,2,1)$	-0.059 (0.39)	0.070 (0.00)	-0.060 (0.04)	0.113	25.88	88:10	0.349
	$(1,2,2)$	-0.073 (0.29)	0.073 (0.00)	-0.075 (0.04)	0.122			0.348
Food away from Home	$(6,1,1)$	0.591 (0.00)	0.024 (0.00)	0.016 (0.29)	0.336	88.50	91:10	0.171
	$(7,2,1)$	0.545 (0.00)	0.027 (0.00)	0.019 (0.20)	0.215			0.340
Electricity	$(3,1,1)$	-1.278 (0.00)	-0.067 (0.43)	-0.027 (0.88)	0.286	–	–	1.957
	$(5,1,2)$	-1.829 (0.00)	-0.096 (0.25)	0.013 (0.31)	0.323			1.911
Services-XFT	$(4,1,1)$	0.415 (0.00)	0.017 (0.07)	0.002 (0.92)	0.106	63.36	95:12	0.217
	$(7,1,1)$	0.523 (0.00)	0.018 (0.05)	0.006 (0.77)	0.144			0.214
Automobile Insurance	$(1,1,1)$	0.068 (0.32)	0.014 (0.76)	0.042 (0.64)	0.007	46.22	97:09	1.079
	$(7,1,1)$	0.493 (0.00)	0.020 (0.66)	-0.020 (0.83)	0.092			1.046
Communication	$(1,1,1)$	-0.089 (0.19)	-0.004 (0.91)	-0.061 (0.37)	0.012	23.93	88:10	0.793
	$(1,1,1)$	-0.089 (0.19)	-0.004 (0.91)	-0.061 (0.37)	0.012			0.793
Local Transportation	$(1,1,1)$	-0.011 (0.87)	-0.010 (0.66)	-0.019 (0.68)	0.002	53.67	92:03	0.536
	$(9,1,4)$	0.461 (0.01)	-0.001 (0.97)	0.113 (0.14)	0.146			0.501
Alcohol in Restaurants	$(3,1,1)$	0.634 (0.00)	0.018 (0.09)	0.007 (0.74)	0.291	53.83	91:08	0.245
	$(8,1,1)$	0.737 (0.00)	0.020 (0.06)	0.009 (0.68)	0.326			0.342
Hotel	$(1,2,1)$	-0.325 (0.00)	0.113 (0.03)	-0.213 (0.20)	0.121	26.29	98:05	1.943
	$(2,2,1)$	-0.462 (0.00)	0.130 (0.01)	-0.243 (0.15)	0.130			1.938
Rent	$(5,1,1)$	0.932 (0.00)	0.007 (0.03)	-0.010 (0.09)	0.690	72.81	89:05	0.070
	$(5,1,1)$	0.932 (0.00)	0.007 (0.03)	-0.010 (0.09)	0.690			0.070
Property Tax	$(5,1,1)$	0.530 (0.00)	-0.000 (0.98)	-0.054 (0.17)	0.109	79.84	93:08	0.445
	$(9,1,1)$	0.741 (0.00)	0.013 (0.52)	-0.069 (0.08)	0.154			0.437

(continued)

Table 4 (*concluded*)

Component	Lag**	$\sum AR$	$\sum gap$	$\sum exc$	R^2	$\sup F(T_B)$	T_B	σ_u
Depreciation	$(4,1,1)$	0.849 (0.00)	−0.002 (0.89)	−0.001 (0.97)	0.525	63.12	90:05	0.351
	$(6,5,1)$	0.845 (0.00)	0.005 (0.09)	−0.013 (0.67)	0.558			0.344
Repairs and other shelter items	$(1,1,1)$	−0.328 (0.00)	0.076 (0.05)	−0.014 (0.86)	0.118	17.43	92:08	0.907
	$(6,1,1)$	−0.637 (0.00)	0.086 (0.03)	−0.001 (0.99)	0.162			0.895
Home Insurance	$(2,1,1)$	0.497 (0.00)	0.019 (0.48)	−0.003 (0.95)	0.184	70.99	90:05	0.608
	$(3,1,3)$	0.517 (0.00)	0.002 (0.97)	0.136 (0.09)	0.215			0.600
Durable Ex. Automobiles	$(6,1,1)$	0.624 (0.00)	0.005 (0.74)	0.040 (0.13)	0.167	62.73	90:01	0.311
	$(7,6,6)$	0.632 (0.00)	0.013 (0.04)	−0.011 (0.03)	0.256			0.302
Automobiles	$(1,1,1)$	0.081 (0.23)	−0.004 (0.88)	−0.116 (0.05)	0.028	41.85	88:11	0.681
	$(1,6,1)$	0.039 (0.57)	−0.034 (0.06)	−0.090 (0.12)	0.081			0.670
Semi-Durable	$(1,1,1)$	−0.242 (0.00)	0.014 (0.45)	0.035 (0.33)	0.062	39.44	92:05	0.425
	$(5,1,9)$	0.253 (0.00)	−0.003 (0.87)	0.135 (0.00)	0.181			0.400
Alcohol	$(3,1,1)$	0.379 (0.00)	0.013 (0.42)	0.014 (0.66)	0.082	72.74	88:08	0.374
	$(5,1,1)$	0.545 (0.00)	0.013 (0.40)	0.005 (0.89)	0.123			0.367
Other Non-Dur.	$(2,1,1)$	0.190 (0.04)	0.046 (0.00)	−0.012 (0.68)	0.092	25.20	95:07	0.336
	$(4,1,2)$	0.358 (0.02)	0.038 (0.01)	−0.077 (0.29)	0.121			0.333
Core PCI	$(4,1,1)$	0.600 (0.00)	0.014 (0.05)	−0.028 (0.04)	0.190	48.25	91:07	0.151
	$(9,1,1)$	0.761 (0.13)	0.014 (0.03)	−0.031 (0.02)	0.250			0.147

* Joint test of significance p–value in parenthesis. Estimates of the constant are not reported.

** The first row refers to the lag selection by SIC; second row refers to AIC.

Table 5: Monthly Data – Results Using the QPM Output-Gap Measure With Break*

Component	Lag**	$\sum AR$	$\sum gap$	$\sum exc$	R^2	Sample starts	σ_u
Other Food	$(1,1,1)$	-0.070 (0.34)	0.065 (0.00)	-0.041 (0.14)	0.100	88:11	0.309
	$(1,2,2)$	-0.101 (0.17)	0.070 (0.00)	-0.064 (0.04)	0.128		0.305
Food away from Home	$(1,1,1)$	0.096 (0.24)	0.014 (0.05)	0.013 (0.30)	0.057	91:11	0.133
	$(7,1,1)$	0.314 (0.01)	0.016 (0.02)	0.015 (0.21)	0.154		0.128
Electricity	$(3,1,1)$	-1.278 (0.00)	-0.067 (0.43)	-0.027 (0.88)	0.286	–	1.957
	$(5,1,2)$	-1.829 (0.00)	-0.096 (0.25)	0.013 (0.31)	0.323		1.911
Services-XFT	$(1,1,1)$	0.083 (0.39)	-0.003 (0.87)	-0.024 (0.19)	0.025	96:01	0.170
	$(2,1,1)$	-0.048 (0.25)	-0.003 (0.86)	-0.020 (0.27)	0.044		0.169
Automobile Insurance	$(1,1,1)$	0.673 (0.00)	0.061 (0.47)	-0.035 (0.68)	0.453	97:10	0.750
	$(1,1,1)$	0.673 (0.00)	0.061 (0.47)	-0.035 (0.68)	0.453		0.750
Communication	$(1,1,1)$	-0.088 (0.20)	-0.022 (0.53)	-0.053 (0.44)	0.016	88:11	0.768
	$(1,1,1)$	-0.088 (0.20)	-0.022 (0.53)	-0.053 (0.44)	0.016		0.768
Local Transportation	$(1,1,1)$	-0.058 (0.50)	-0.008 (0.81)	0.032 (0.54)	0.006	93:04	0.541
	$(9,5,1)$	-0.084 (0.00)	0.029 (0.03)	0.061 (0.23)	0.240		0.500
Alcohol in Restaurants	$(3,1,1)$	0.388 (0.00)	0.006 (0.53)	0.013 (0.44)	0.112	91:09	0.181
	$(3,1,1)$	0.388 (0.00)	0.006 (0.53)	0.013 (0.44)	0.112		0.181
Hotel	$(1,2,1)$	-0.412 (0.00)	0.513 (0.01)	-0.204 (0.42)	0.245	98:06	1.818
	$(2,6,5)$	-1.094 (0.00)	1.770 (0.00)	0.236 (0.09)	0.547		1.558
Rent	$(4,1,1)$	0.900 (0.00)	0.004 (0.19)	-0.009 (0.12)	0.715	89:06	0.060
	$(5,1,1)$	0.907 (0.00)	0.004 (0.14)	-0.010 (0.09)	0.721		0.059
Property Tax	$(1,1,1)$	-0.154 (0.08)	-0.059 (0.00)	0.015 (0.59)	0.072	93:09	0.289
	$(1,1,1)$	-0.154 (0.08)	-0.059 (0.00)	0.015 (0.59)	0.072		0.289

(continued)

Table 5 (*concluded*)

Component	Lag**	$\sum AR$	$\sum gap$	$\sum exc$	R^2	Sample starts	σ_u
Depreciation	$(6,1,1)$	0.690 (0.00)	0.005 (0.75)	0.000 (0.98)	0.456	90:06	0.288
	$(6,5,1)$	0.676 (0.00)	0.015 (0.09)	0.010 (0.71)	0.487		0.283
Repairs and other shelter items	$(1,1,1)$	−0.346 (0.00)	0.087 (0.09)	0.010 (0.91)	0.130	92:09	0.903
	$(2,2,9)$	−0.636 (0.00)	0.090 (0.06)	0.148 (0.06)	0.255		0.867
Home Insurance	$(1,1,1)$	0.310 (0.00)	0.041 (0.13)	0.010 (0.86)	0.124	90:06	0.590
	$(3,2,3)$	0.406 (0.00)	0.011 (0.06)	0.184 (0.03)	0.207		0.569
Durable Ex. Automobiles	$(2,1,1)$	−0.181 (0.04)	0.008 (0.56)	0.020 (0.47)	0.043	90:02	0.292
	$(7,1,5)$	0.135 (0.00)	0.006 (0.64)	−0.063 (0.03)	0.169		0.279
Automobiles	$(1,1,1)$	0.095 (0.19)	−0.018 (0.48)	−0.099 (0.05)	0.040	88:12	0.569
	$(1,1,1)$	0.095 (0.19)	−0.034 (0.62)	−0.099 (0.05)	0.040		0.569
Semi-Durable	$(1,1,1)$	−0.341 (0.00)	−0.008 (0.76)	−0.018 (0.67)	0.119	92:06	0.439
	$(1,1,8)$	−0.352 (0.00)	−0.001 (0.72)	−0.025 (0.00)	0.253		0.415
Alcohol	$(1,4,1)$	−0.039 (0.57)	0.005 (0.00)	0.006 (0.82)	0.087	88:09	0.279
	$(3,4,1)$	0.157 (0.03)	0.004 (0.00)	0.001 (0.97)	0.130		0.274
Other Non-Dur.	$(1,1,1)$	0.018 (0.84)	0.026 (0.30)	−0.024 (0.38)	0.019	95:08	0.252
	$(4,2,1)$	0.105 (0.14)	0.027 (0.22)	−0.041 (0.18)	0.105		0.245
Core CPI	$(1,1,1)$	−0.088 (0.26)	0.005 (0.46)	−0.021 (0.12)	0.024	91:08	0.146
	$(1,1,1)$	−0.088 (0.26)	0.005 (0.46)	−0.021 (0.12)	0.024		0.146

*Joint test of significance p–value in parenthesis. Estimates of the constant are not reported.

**The first row refers to the lag selection by SIC; second row refers to AIC.

Table 6: Quarterly Data – Estimation Results Using the QPM Output-Gap Measure*

Component	Lag**	$\sum AR$	$\sum gap$	$\sum exc$	R^2	$\sup F(T_B)$	T_B	σ_u
Durable	$(2,3,1)$	0.589 (0.00)	−0.035 (0.03)	−0.025 (0.48)	0.374	45.37	89:4	0.560
	$(2,3,1)$	0.589 (0.00)	−0.035 (0.03)	−0.025 (0.48)	0.374			0.560
Semi-Durable	$(2,1,1)$	0.606 (0.00)	0.018 (0.66)	−0.014 (0.86)	0.270	32.82	92:3	0.509
	$(2,1,4)$	0.555 (0.00)	0.000 (0.99)	0.092 (0.12)	0.349			0.492
Non-Durable-X	$(1,1,1)$	0.621 (0.00)	0.056 (0.05)	−0.001 (0.98)	0.486	36.86	92:3	0.340
	$(1,1,1)$	0.621 (0.00)	0.056 (0.05)	−0.001 (0.98)	0.486			0.340
Food-X	$(1,1,1)$	0.430 (0.00)	0.110 (0.00)	−0.025 (0.26)	0.461	14.18	93:1	0.343
	$(1,1,4)$	0.495 (0.00)	0.105 (0.00)	−0.024 (0.02)	0.541			0.328
Electricity	$(3,1,1)$	0.263 (0.00)	−0.084 (0.49)	0.082 (0.41)	0.367	–	–	1.532
	$(4,4,2)$	0.022 (0.00)	0.087 (0.10)	−0.070 (0.37)	0.465			1.465
Services-X	$(1,1,1)$	0.311 (0.01)	0.043 (0.18)	0.010 (0.70)	0.153	18.06	93:3	0.414
	$(3,1,1)$	0.465 (0.00)	0.053 (0.11)	0.006 (0.91)	0.199			0.409
Shelter-X	$(3,1,1)$	0.851 (0.00)	0.003 (0.90)	0.018 (0.34)	0.684	22.81	90:2	0.288
	$(3,1,1)$	0.851 (0.00)	0.003 (0.90)	0.018 (0.34)	0.684			0.288
Core CPI	$(3,1,1)$	0.788 (0.00)	0.035 (0.07)	−0.015 (0.36)	0.528	24.85	92:1	0.233
	$(3,1,1)$	0.788 (0.00)	0.035 (0.07)	−0.015 (0.36)	0.528			0.233

* Joint test of significance p–value in parenthesis. Estimates of the constant are not reported.

** The first row refers to the lag selection by SIC; second row refers to AIC.

Table 7: Quarterly Data – Estimation Results Using the QPM Output-Gap Measure With Break*

Component	Lag**	$\sum AR$	$\sum gap$	$\sum exc$	R^2	Sample starts	σ_u
Durable	$(2,1,1)$	0.571 (0.00)	-0.038 (0.33)	-0.037 (0.27)	0.299	90:1	0.486
	$(2,1,1)$	0.571 (0.00)	-0.038 (0.33)	-0.037 (0.27)	0.299		0.486
Semi-Durable	$(1,1,1)$	-0.078 (0.61)	-0.017 (0.71)	-0.046 (0.16)	0.055	92:4	0.471
	$(4,2,4)$	-0.485 (0.23)	-0.046 (0.13)	0.010 (0.10)	0.331		0.431
Non-Durable-X	$(2,2,2)$	0.119 (0.02)	0.045 (0.02)	-0.053 (0.05)	0.382	92:4	0.318
	$(3,2,2)$	-0.066 (0.01)	0.032 (0.01)	-0.047 (0.11)	0.422		0.311
Food-X	$(1,1,1)$	0.206 (0.13)	0.080 (0.02)	-0.026 (0.21)	0.234	93:2	0.293
	$(1,2,1)$	0.126 (0.37)	0.095 (0.01)	-0.035 (0.10)	0.291		0.285
Electricity	$(1,1,1)$	0.181 (0.25)	0.019 (0.68)	0.082 (0.41)	0.367	–	1.532
	$(4,4,2)$	0.022 (0.00)	0.087 (0.10)	-0.070 (0.37)	0.465		1.465
Services-X	$(1,1,1)$	0.181 (0.25)	0.019 (0.68)	0.013 (0.65)	0.046	93:4	0.404
	$(1,1,1)$	0.181 (0.25)	0.019 (0.68)	0.013 (0.65)	0.046		0.404
Shelter-X	$(3,1,1)$	0.663 (0.00)	-0.011 (0.61)	0.019 (0.31)	0.483	90:3	0.260
	$(3,3,1)$	0.621 (0.00)	0.007 (0.09)	0.018 (0.48)	0.543		0.249
Core CPI	$(1,1,1)$	-0.023 (0.86)	0.011 (0.58)	-0.014 (0.37)	0.020	92:2	0.220
	$(1,1,1)$	-0.023 (0.86)	0.011 (0.58)	-0.014 (0.37)	0.020		0.220

*Joint test of significance p–value in parenthesis. Estimates of the constant are not reported.

** The first row refers to the lag selection by SIC; second row refers to AIC.

Table 8: Quarterly Data – Estimation Results Using the QPM Output-Gap Measure*

Component	Lag**	$\sum AR$	$\sum gap$	$\sum exc$	R^2	$\sup F(T_B)$	T_B	σ_u
Other Food	$(1,1,3)$	0.386 (0.00)	0.149 (0.00)	−0.095 (0.01)	0.448	11.13	97:4	0.455
	$(4,1,4)$	0.247 (0.00)	0.134 (0.00)	−0.029 (0.10)	0.530			0.433
Food away from Home	$(2,1,1)$	0.733 (0.00)	0.068 (0.00)	−0.012 (0.40)	0.677	38.31	94:1	0.221
	$(2,3,1)$	0.764 (0.00)	0.058 (0.00)	−0.011 (0.45)	0.695			0.218
Electricity	$(3,1,1)$	0.263 (0.00)	−0.084 (0.49)	0.082 (0.41)	0.367	–	–	1.532
	$(4,4,2)$	0.022 (0.00)	0.087 (0.10)	−0.070 (0.37)	0.465			1.465
Services-XFT	$(4,1,1)$	0.798 (0.00)	0.061 (0.01)	−0.015 (0.44)	0.483	40.36	93:3	0.285
	$(4,1,1)$	0.798 (0.00)	0.061 (0.01)	−0.015 (0.44)	0.483			0.285
Automobile Insurance	$(1,1,1)$	0.523 (0.00)	0.043 (0.72)	−0.028 (0.78)	0.271	12.93	98:2	1.567
	$(4,1,1)$	0.421 (0.00)	0.031 (0.79)	−0.006 (0.95)	0.353			1.510
Communication	$(1,1,1)$	0.030 (0.81)	−0.021 (0.83)	−0.024 (0.77)	0.004	27.91	90:4	1.315
	$(1,1,1)$	0.030 (0.81)	−0.021 (0.83)	−0.024 (0.77)	0.004			1.315
Local Transportation	$(1,1,1)$	0.448 (0.00)	−0.032 (0.54)	0.083 (0.05)	0.269	31.26	93:2	0.536
	$(1,1,4)$	0.367 (0.00)	−0.068 (0.21)	0.221 (0.02)	0.354			0.640
Alcohol in Restaurants	$(3,1,1)$	0.768 (0.00)	0.068 (0.03)	−0.000 (0.99)	0.619	37.61	92:3	0.396
	$(3,1,1)$	0.768 (0.00)	0.068 (0.03)	−0.000 (0.99)	0.619			0.396
Hotel	$(1,1,1)$	0.097 (0.43)	0.209 (0.25)	−0.246 (0.09)	0.070	51.00	98:4	2.273
	$(4,4,1)$	0.361 (0.00)	−0.094 (0.02)	−0.186 (0.18)	0.260			2.125
Rent	$(1,1,1)$	0.926 (0.00)	0.010 (0.15)	0.006 (0.34)	0.917	34.75	92:4	0.092
	$(1,2,2)$	0.930 (0.00)	0.007 (0.17)	0.013 (0.19)	0.922			0.091
Property Tax	$(2,1,1)$	0.631 (0.00)	−0.013 (0.83)	0.032 (0.52)	0.306	36.09	94:2	0.750
	$(4,2,4)$	0.753 (0.00)	0.021 (0.40)	0.055 (0.07)	0.447			0.702

(continued)

Table 8 (*concluded*)

Component	Lag**	$\sum AR$	$\sum gap$	$\sum exc$	R^2	$\sup F(T_B)$	T_B	σ_u
Depreciation	$(1,1,1)$	0.727 (0.00)	0.002 (0.98)	0.047 (0.39)	0.571	35.31	91:2	0.845
	$(1,3,1)$	0.732 (0.00)	0.046 (0.15)	0.032 (0.55)	0.604			0.829
Repairs and other shelter items	$(1,1,1)$	0.135 (0.25)	0.112 (0.14)	0.078 (0.13)	0.128	15.20	95:3	0.957
	$(2,4,2)$	−0.168 (0.09)	0.236 (0.06)	0.059 (0.19)	0.249			0.917
Home Insurance	$(1,1,1)$	0.556 (0.00)	0.008 (0.93)	0.083 (0.26)	0.344	26.18	89:3	1.151
	$(3,1,1)$	0.621 (0.00)	−0.018 (0.84)	0.099 (0.18)	0.381			1.135
Durable Ex. Automobiles	$(1,1,1)$	0.620 (0.00)	0.032 (0.37)	0.003 (0.92)	0.431	38.79	90:3	0.440
	$(2,1,4)$	0.733 (0.00)	0.027 (0.42)	−0.041 (0.05)	0.529			0.413
Automobiles	$(1,3,1)$	0.266 (0.02)	−0.092 (0.03)	−0.082 (0.21)	0.253	56.83	89:4	0.994
	$(2,3,1)$	0.394 (0.02)	−0.078 (0.03)	−0.099 (0.12)	0.283			0.982
Semi-Durable	$(2,1,1)$	0.606 (0.00)	0.018 (0.66)	−0.056 (0.86)	0.270	32.82	92:3	0.509
	$(2,1,4)$	0.555 (0.00)	0.000 (0.99)	0.092 (0.12)	0.349			0.492
Alcohol	$(3,1,1)$	0.688 (0.00)	0.054 (0.20)	−0.016 (0.65)	0.407	67.83	89:3	0.533
	$(3,1,4)$	0.616 (0.00)	0.030 (0.46)	0.098 (0.03)	0.498			0.502
Other Non-Dur.	$(1,1,1)$	0.465 (0.00)	0.091 (0.03)	0.022 (0.50)	0.366	32.53	96:1	0.511
	$(1,1,1)$	0.465 (0.00)	0.091 (0.03)	0.022 (0.50)	0.366			0.511
Core CPI	$(3,1,1)$	0.788 (0.00)	0.035 (0.07)	−0.015 (0.36)	0.528	24.85	92:1	0.233
	$(3,1,1)$	0.788 (0.00)	0.035 (0.07)	−0.015 (0.36)	0.528			0.233

*Joint test of significance p–value in parenthesis. Estimates of the constant are not reported.

**The first row refers to the lag selection by SIC; second row refers to AIC.

Table 9: Quarterly Data – Estimation Results Using the QPM Output-Gap Measure With Break*

Component	Lag**	$\sum AR$	$\sum gap$	$\sum exc$	R^2	Sample starts	σ_u
Other Food	$(1,2,1)$	-0.006 (0.97)	0.308 (0.00)	-0.055 (0.05)	0.574	98:1	0.330
	$(1,2,1)$	-0.006 (0.97)	0.308 (0.00)	-0.055 (0.05)	0.574		0.330
Food away from Home	$(2,2,1)$	0.303 (0.07)	0.077 (0.01)	-0.014 (0.32)	0.453	94:2	0.182
	$(2,2,1)$	0.303 (0.07)	0.077 (0.01)	-0.014 (0.32)	0.453		0.182
Electricity	$(3,1,1)$	0.263 (0.00)	-0.084 (0.49)	0.082 (0.41)	0.367	–	1.532
	$(4,4,2)$	0.022 (0.00)	0.087 (0.10)	-0.070 (0.37)	0.465		1.465
Services-XFT	$(1,1,1)$	-0.075 (0.62)	0.022 (0.36)	-0.006 (0.70)	0.023	93:4	0.219
	$(2,1,3)$	-0.328 (0.23)	0.026 (0.30)	-0.016 (0.20)	0.173		0.210
Automobile Insurance	$(4,1,1)$	0.371 (0.00)	-0.090 (0.80)	0.145 (0.43)	0.706	98:3	1.537
	$(4,1,1)$	0.371 (0.00)	0.371 (0.00)	0.145 (0.43)	0.706		1.537
Communication	$(1,1,1)$	0.086 (0.52)	0.029 (0.76)	0.047 (0.54)	0.018	91:1	1.137
	$(1,1,1)$	0.086 (0.52)	0.029 (0.76)	0.047 (0.54)	0.018		1.137
Local Transportation	$(1,2,1)$	0.139 (0.27)	-0.181 (0.03)	-0.037 (0.11)	0.298	93:3	0.562
	$(1,2,1)$	0.139 (0.27)	-0.181 (0.03)	-0.037 (0.11)	0.298		0.562
Alcohol in Restaurants	$(1,1,1)$	0.547 (0.00)	0.030 (0.22)	0.019 (0.29)	0.409	92:4	0.259
	$(3,1,1)$	0.571 (0.00)	0.038 (0.12)	0.015 (0.40)	0.458		0.254
Hotel	$(4,2,2)$	0.562 (0.00)	-0.045 (0.01)	0.248 (0.02)	0.740	99:1	1.788
	$(4,2,1)$	0.562 (0.00)	-0.045 (0.01)	0.248 (0.02)	0.740		1.788
Rent	$(1,1,1)$	0.785 (0.00)	0.002 (0.80)	-0.004 (0.39)	0.751	93:1	0.061
	$(1,4,1)$	0.792 (0.00)	0.005 (0.14)	-0.007 (0.11)	0.789		0.058
Property Tax	$(1,1,1)$	-0.109 (0.52)	-0.131 (0.05)	-0.001 (0.96)	0.098	94:3	0.458
	$(1,1,1)$	-0.109 (0.52)	-0.131 (0.05)	-0.001 (0.96)	0.098		0.458

(continued)

Table 9 (*concluded*)

Component	Lag**	$\sum AR$	$\sum gap$	$\sum exc$	R^2	Sample starts	σ_u
Depreciation	$(1,1,1)$	0.606 (0.00)	0.016 (0.82)	-0.007 (0.87)	0.360	91:3	0.741
	$(2,3,1)$	0.470 (0.00)	0.092 (0.04)	0.018 (0.71)	0.481		0.688
Repairs and other shelter items	$(2,1,1)$	0.391 (0.08)	0.063 (0.57)	-0.032 (0.54)	0.156	95:4	0.666
	$(1,4,2)$	0.194 (0.22)	0.213 (0.05)	0.034 (0.09)	0.338		0.619
Home Insurance	$(1,1,1)$	0.511 (0.00)	0.020 (0.82)	0.074 (0.31)	0.284	89:4	1.056
	$(3,1,1)$	0.597 (0.00)	-0.005 (0.95)	0.094 (0.18)	0.368		1.009
Durable Ex. Automobiles	$(1,1,2)$	0.330 (0.01)	0.022 (0.49)	-0.055 (0.04)	0.220	90:4	0.370
	$(1,1,4)$	0.352 (0.00)	0.019 (0.54)	-0.081 (0.03)	0.280		0.363
Automobiles	$(2,1,1)$	0.503 (0.00)	-0.078 (0.24)	-0.105 (0.06)	0.301	90:1	0.809
	$(2,1,1)$	0.503 (0.00)	-0.078 (0.24)	-0.105 (0.06)			0.809
Semi-Durable	$(1,1,1)$	-0.078 (0.61)	-0.017 (0.71)	-0.046 (0.16)	0.055	92:4	0.471
	$(4,2,4)$	-0.485 (0.23)	-0.046 (0.13)	0.010 (0.10)	0.331		0.431
Alcohol	$(1,2,1)$	0.555 (0.07)	0.034 (0.04)	-0.021 (0.42)	0.476	89:4	0.363
	$(1,2,4)$	0.438 (0.00)	0.013 (0.07)	0.068 (0.03)	0.562		0.341
Other Non-Dur.	$(4,1,1)$	-0.136 (0.01)	0.041 (0.42)	-0.027 (0.27)	0.420	96:2	0.286
	$(4,1,1)$	-0.136 (0.01)	0.041 (0.42)	-0.027 (0.27)	0.420		0.286
Core CPI	$(1,1,1)$	-0.023 (0.88)	0.011 (0.58)	-0.014 (0.37)	0.020	92:1	0.220
	$(1,1,1)$	-0.023 (0.88)	0.011 (0.58)	-0.014 (0.37)	0.020		0.220

*Joint test of significance p–value in parenthesis. Estimates of the constant are not reported.

**The first row refers to the lag selection by SIC; second row refers to AIC.

Table 10: Core Inflation Forecasts – RMSFEs From Monthly Models

Models	Gap Measure / h	1	2	4	8	12	24	One-Quarter
				Aggregate Data				
RW	–	0.2589	0.2546	0.2649	0.2243	0.2403	0.2506	0.3883
				Lag Selection: BIC				
AR	–	0.1891	0.1865	0.1843	0.1844	0.1894	0.2023	0.2899
ARX	QPM	0.1893	0.1873	0.1876	0.1885	0.1943	0.2129	0.2984
	Total–Sectoral	0.1917	0.1900	0.1919	0.1968	0.2046	0.2263	0.3084
ARX-K	QPM	0.1854	0.1844	0.1823	0.1812	0.1865	0.2010	0.2710
	Total–Sectoral	0.1857	0.1846	0.1825	0.1806	0.1857	0.2004	0.2697
Combined	QPM	0.1898	0.1887	0.1897	0.1818	0.1910	0.2074	0.2825
	Total–Sectoral	0.1903	0.1891	0.1903	0.1826	0.1919	0.2087	0.2843
				Lag Selection: AIC				
AR	–	0.1867	0.1853	0.1859	0.1854	0.1909	0.2062	0.2730
ARX	QPM	0.1868	0.1862	0.1877	0.1839	0.1889	0.2108	0.2772
	Total–Sectoral	0.1889	0.1881	0.1898	0.1871	0.1929	0.2194	0.2846
ARX-K	QPM	0.1878	0.1867	0.1923	0.1798	0.1865	0.2014	0.2726
	Total–Sectoral	0.1878	0.1866	0.1841	0.1792	0.1856	0.2007	0.2721
Combined	QPM	0.1879	0.1881	0.1923	0.1845	0.1901	0.2079	0.2718
	Total–Sectoral	0.1884	0.1885	0.1926	0.1818	0.1905	0.2087	0.2734

(continued)

Table 10: (*contined*)

Models	Gap Measure / h	1	2	4	8	12	24	One-Quarter
Disaggregate Data: Level 1								
RW	–	0.2228	0.2218	0.2162	0.2081	0.2180	0.2459	0.3085
Lag Selection: BIC								
AR	–	0.1794	0.1780	0.1776	0.1799	0.1887	0.2017	0.2528
ARX	QPM	0.1777	0.1795	0.1801	0.1819	0.1928	0.2042	0.2521
	Total	0.1825	0.1831	0.1836	0.1871	0.1981	0.2093	0.2676
	Sectoral	0.1793	0.1803	0.1811	0.1838	0.1949	0.2080	0.2581
ARX-K	QPM	0.1768	0.1795	0.1803	0.1819	0.1928	0.2042	0.2523
	Total	0.1725	0.1809	0.1809	0.1816	0.1905	0.2029	0.2458
	Sectoral	0.1688	0.1802	0.1836	0.1811	0.1838	0.2080	0.2323
Combined	QPM	0.1770	0.1765	0.1788	0.1795	0.1909	0.2072	0.2478
	Total	0.1767	0.1774	0.1795	0.1803	0.1911	0.2082	0.2490
	Sectoral	0.1751	0.1767	0.1794	0.1791	0.1891	0.2100	0.2431
Lag Selection: AIC								
AR	–	0.1902	0.1998	0.1999	0.1841	0.1895	0.2017	0.2482
ARX	QPM	0.2011	0.2091	0.2082	0.1904	0.1957	0.2092	0.2755
	Total	0.2003	0.2093	0.2093	0.1931	0.1971	0.2162	0.2736
	Sectoral	0.1961	0.2057	0.2047	0.1876	0.1908	0.2058	0.2625
ARX-K	QPM	0.1987	0.2076	0.2069	0.1898	0.1926	0.2081	0.2755
	Total	0.1900	0.2080	0.2076	0.1883	0.1891	0.2043	0.2518
	Sectoral	0.1858	0.2072	0.2089	0.1851	0.1847	0.2166	0.2412
Combined	QPM	0.1892	0.1976	0.1950	0.1837	0.1909	0.2097	0.2523
	Total	0.1871	0.1975	0.1948	0.1837	0.1898	0.2088	0.2477
	Sectoral	0.1850	0.1963	0.1939	0.1816	0.1867	0.2096	0.2412

Table 10 (concluded)

Models	Gap Measure / h	1	2	4	8	12	24	One-Quarter
Disaggregate Data: Level 2								
RW	–	0.2253	0.2255	0.2085	0.2116	0.2195	0.2378	0.3231
Lag Selection: BIC								
AR	–	0.1794	0.1780	0.1776	0.1799	0.1887	0.2017	0.2528
ARX	QPM	0.1803	0.1790	0.1794	0.1808	0.1909	0.2026	0.2547
	Total	0.1852	0.1822	0.1827	0.1852	0.1954	0.2074	0.2728
	Sectoral	0.1826	0.1799	0.1803	0.1820	0.1924	0.2055	0.2642
ARX-K	QPM	0.1692	0.1786	0.1824	0.1798	0.1894	0.2047	0.2304
	Total	0.1712	0.1782	0.1818	0.1812	0.1903	0.2040	0.2367
	Sectoral	0.1700	0.1766	0.1836	0.1819	0.1882	0.2134	0.2326
Combined	QPM	0.1765	0.1771	0.1780	0.1802	0.1901	0.2049	0.2454
	Total	0.1779	0.1776	0.1783	0.1813	0.1912	0.2063	0.2512
	Sectoral	0.1770	0.1765	0.1779	0.1801	0.1892	0.2068	0.2480
Lag Selection: AIC								
AR	–	0.1929	0.2004	0.2006	0.1830	0.1882	0.2019	0.2463
ARX	QPM	0.2007	0.2076	0.2078	0.1853	0.1900	0.2034	0.2670
	Total	0.2010	0.2078	0.2079	0.1877	0.1919	0.2060	0.2695
	Sectoral	0.1984	0.2056	0.2053	0.1853	0.1897	0.2090	0.2603
ARX-K	QPM	0.1870	0.2057	0.2109	0.1853	0.2053	0.2072	0.2545
	Total	0.1898	0.2067	0.2140	0.1909	0.2048	0.2086	0.2442
	Sectoral	0.1896	0.2061	0.2164	0.1997	0.2059	0.2101	0.2345
Combined	QPM	0.1865	0.1969	0.1934	0.1816	0.1898	0.2041	0.2395
	Total	0.1876	0.1971	0.1939	0.1828	0.1930	0.2045	0.2414
	Sectoral	0.1871	0.1963	0.1935	0.1905	0.1918	0.2048	0.2379

Table 11: Core Inflation Forecasts – RMSFE's From Quarterly Models

Models	Gap Measure / h	1	2	4	8
		Aggregate Data			
RW	–	0.3618	0.3140	0.3245	0.3995
		Lag Selection: BIC and AIC			
AR	–	0.3007	0.3041	0.2961	0.3384
ARX	QPM	0.3053	0.3100	0.2890	0.3287
	Total–Sectoral	0.3135	0.3242	0.3068	0.3536
ARX-K	QPM	0.2981	0.2892	0.2826	0.3072
	Total–Sectoral	0.2994	0.3054	0.2985	0.3326
Combined	QPM	0.2973	0.2810	0.2602	0.3249
	Total–Sectoral	0.3034	0.2905	0.2683	0.3367
		Disaggregate Data: Level 1			
RW	–	0.3501	0.3218	0.3162	0.3581
		Lag Selection: BIC			
AR	–	0.2552	0.2720	0.2930	0.3270
ARX	QPM	0.2756	0.2962	0.3282	0.3467
	Total	0.2717	0.2962	0.3211	0.3441
	Sectoral	0.2645	0.2849	0.3063	0.3276
ARX-K	QPM	0.2732	0.2913	0.3116	0.3377
	Total	0.2632	0.2778	0.2964	0.3282
	Sectoral	0.2556	0.2680	0.2878	0.3221
Combined	QPM	0.2676	0.2673	0.3043	0.3307
	Total	0.2661	0.2653	0.2992	0.3272
	Sectoral	0.2625	0.2598	0.2933	0.3216

(continued)

Table 11 (*continued*)

Lag Selection: AIC					
AR	–	0.2638	0.2816	0.3008	0.3343
ARX	QPM	0.2768	0.2932	0.3223	0.3461
	Total	0.3121	0.3297	0.3571	0.3940
	Sectoral	0.3135	0.3242	0.3068	0.3536
ARX-K	QPM	0.2855	0.3060	0.3111	0.3373
	Total	0.2841	0.2987	0.3056	0.3457
	Sectoral	0.2994	0.3054	0.2985	0.3326
Combined	QPM	0.2727	0.2726	0.3049	0.3303
	Total	0.2790	0.2779	0.3079	0.3425
	Sectoral	0.3034	0.2905	0.2683	0.3367

(***continued***)

Table 11 (*concluded*)

Models	Gap Measure / h	1	2	4	8
Disaggregate Data: Level 2					
RW	–	0.3269	0.2971	0.3464	0.3873
Lag Selection: BIC					
AR	–	0.2556	0.2794	0.2917	0.3092
ARX	QPM	0.2648	0.2895	0.3077	0.3296
	Total	0.2714	0.3076	0.3267	0.3505
	Sectoral	0.2624	0.2937	0.3115	0.3337
ARX-K	QPM	0.2561	0.2993	0.3072	0.3089
	Total	0.2533	0.3059	0.3321	0.3031
	Sectoral	0.2563	0.3144	0.3092	0.3130
Combined	QPM	0.2605	0.2689	0.2931	0.3087
	Total	0.2612	0.2741	0.3004	0.3193
	Sectoral	0.2602	0.2725	0.2926	0.3194
Lag Selection: AIC					
AR	–	0.2663	0.2860	0.2995	0.3123
ARX	QPM	0.2794	0.3031	0.3181	0.3288
	Total	0.3102	0.3422	0.3603	0.3847
	Sectoral	0.2771	0.3081	0.3235	0.3406
ARX-K	QPM	0.2644	0.3081	0.2634	0.3306
	Total	0.2848	0.3084	0.2695	0.3103
	Sectoral	0.2731	0.3245	0.3021	0.3251
Combined	QPM	0.2663	0.2712	0.2818	0.3245
	Total	0.2759	0.2797	0.2849	0.3404
	Sectoral	0.2692	0.2798	0.3011	0.3341

Figure 1: **Some CPI Components**

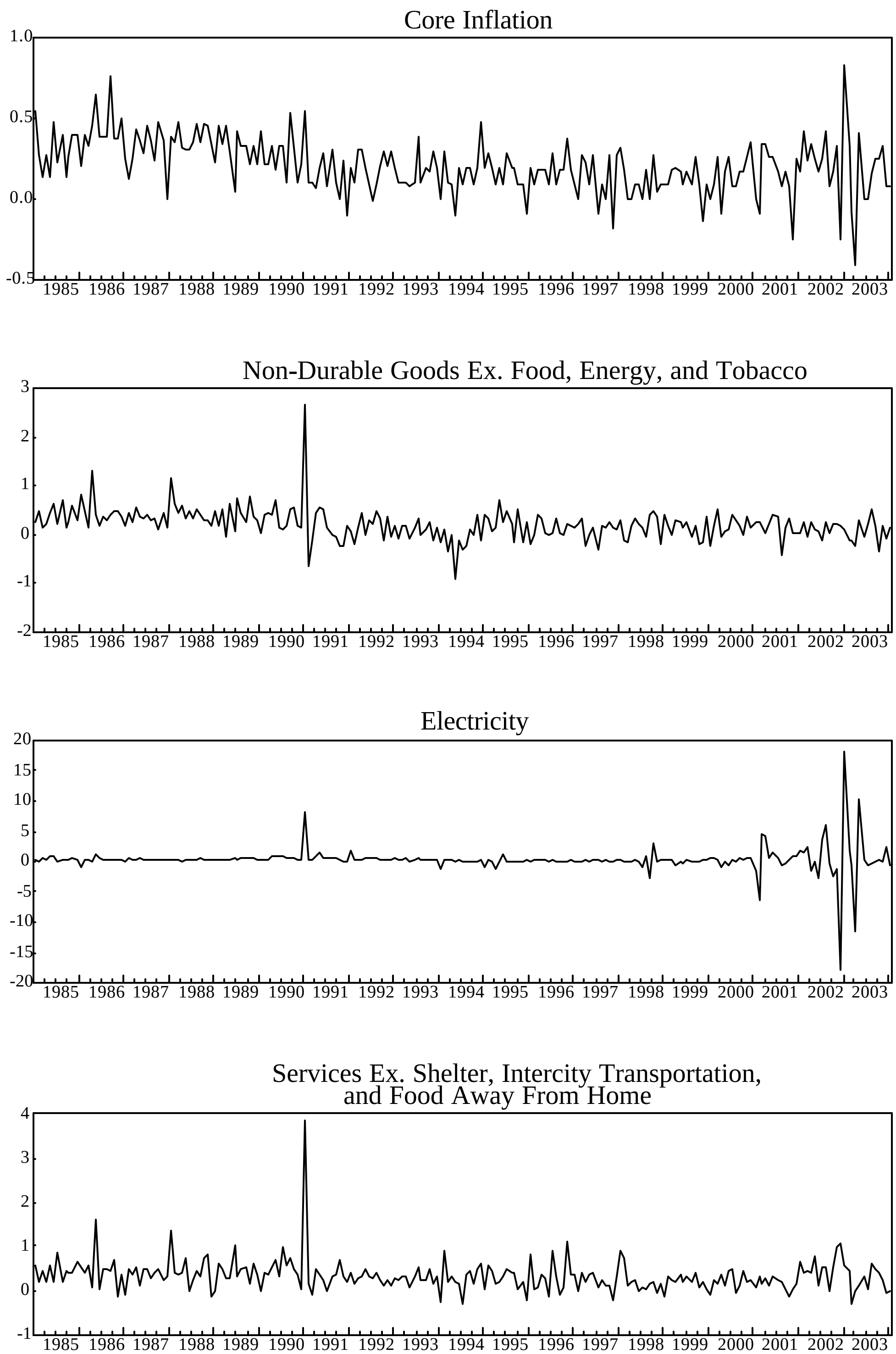


Figure 2: **Some CPI Components**

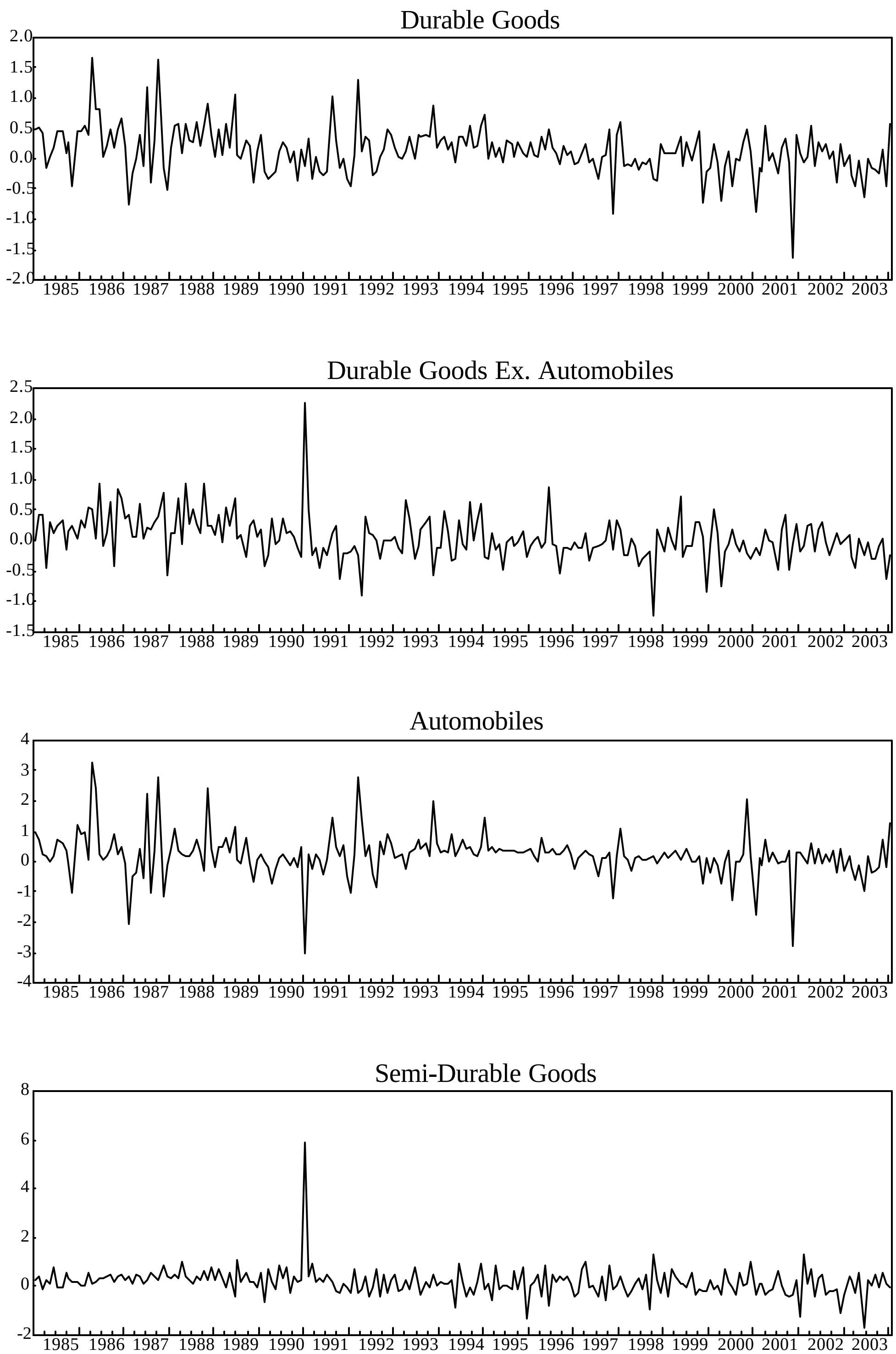


Figure 3: **Some CPI Components**

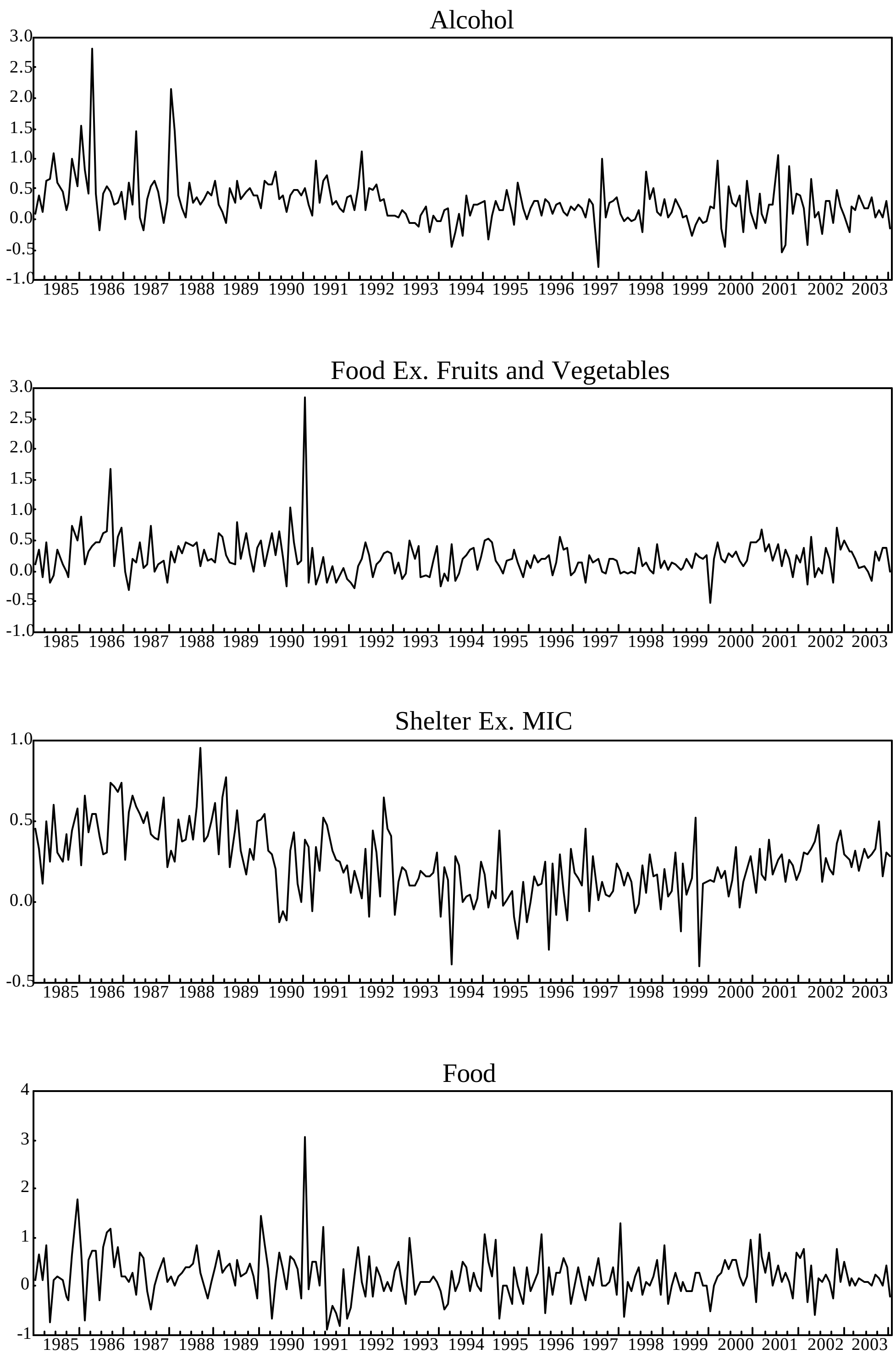


Figure 4: **Some CPI Components**

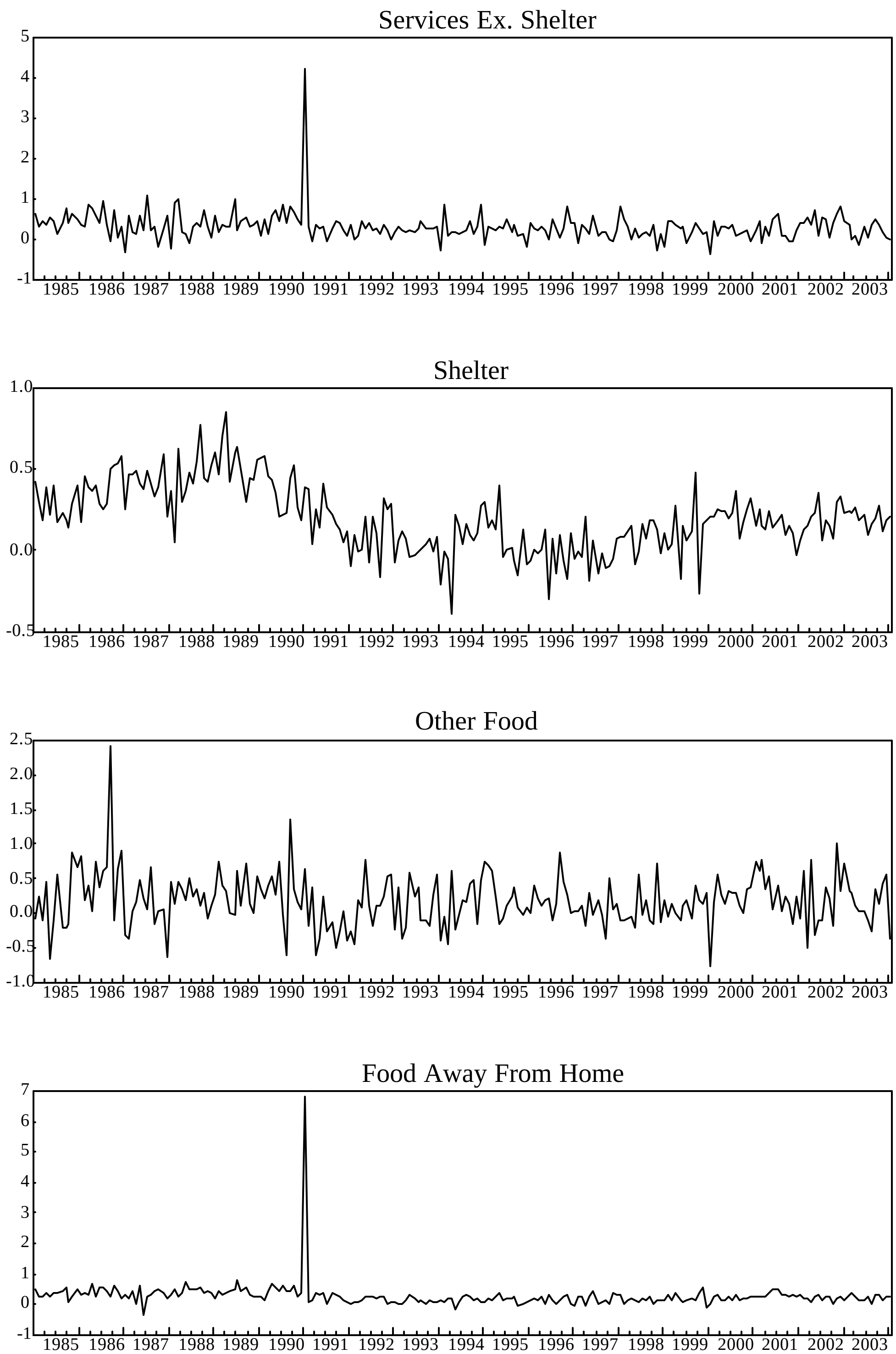


Figure 5: **Some CPI Components**

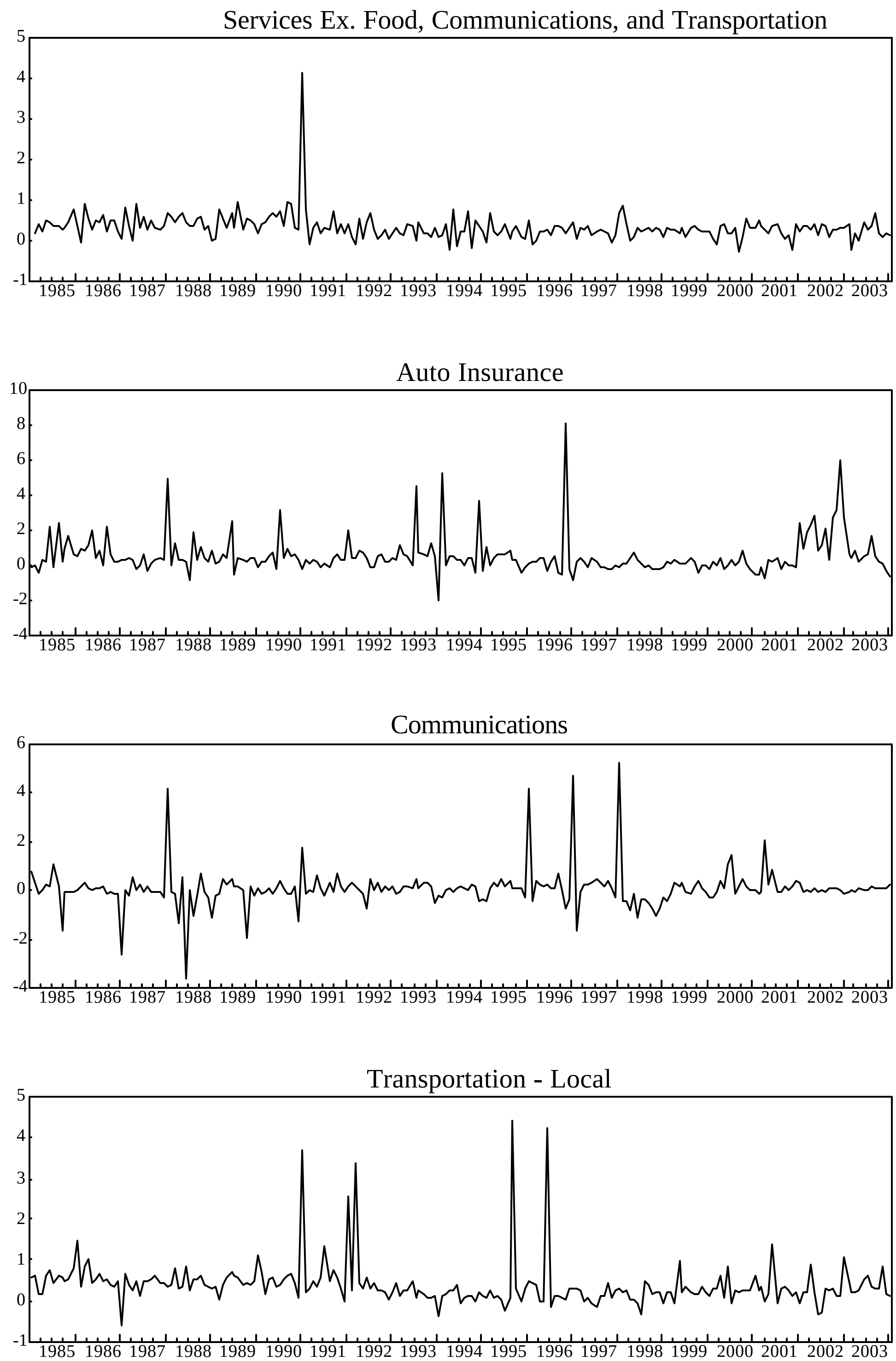


Figure 6: **Some CPI Components**

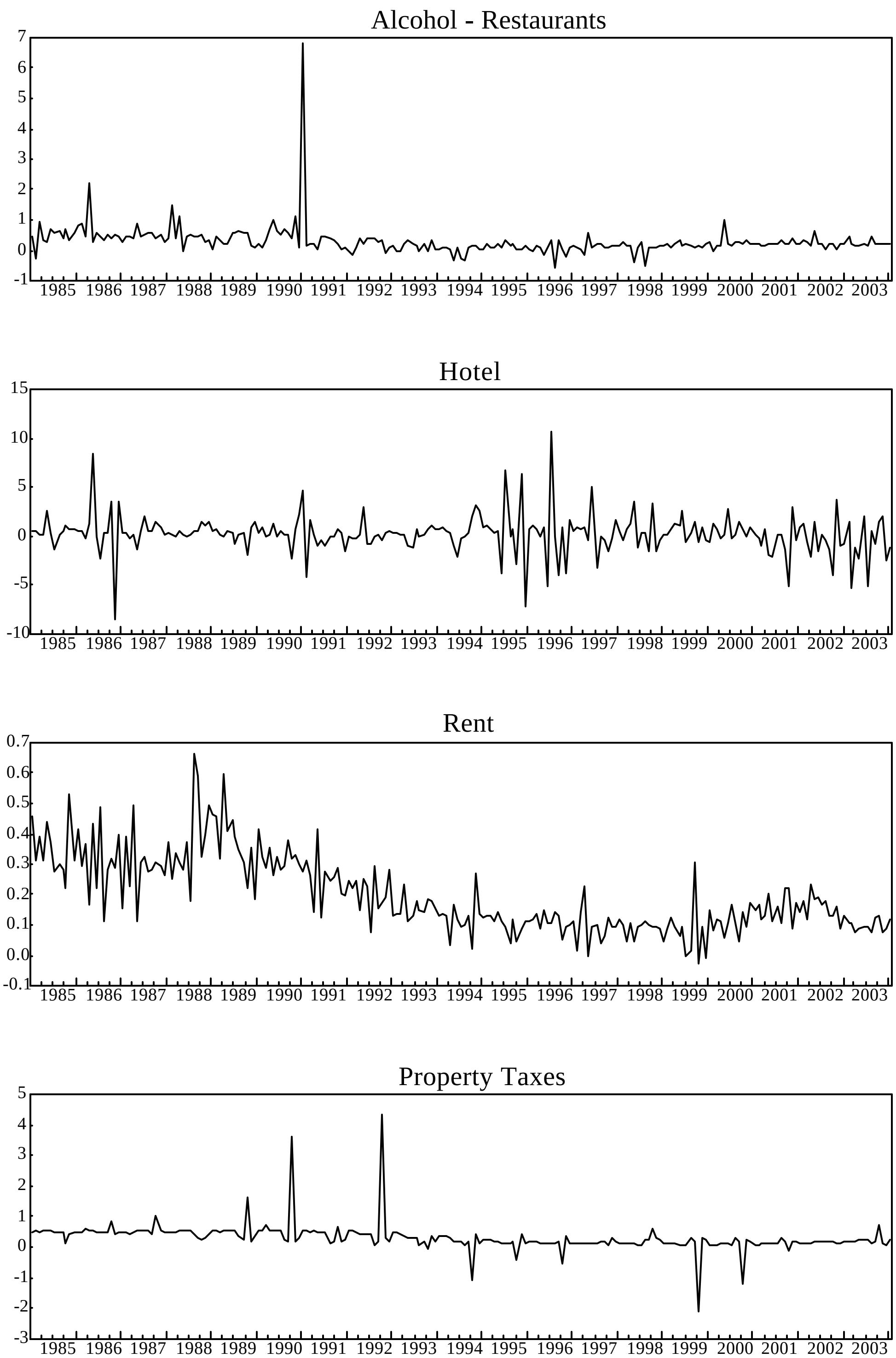


Figure 7: **Some CPI Components**

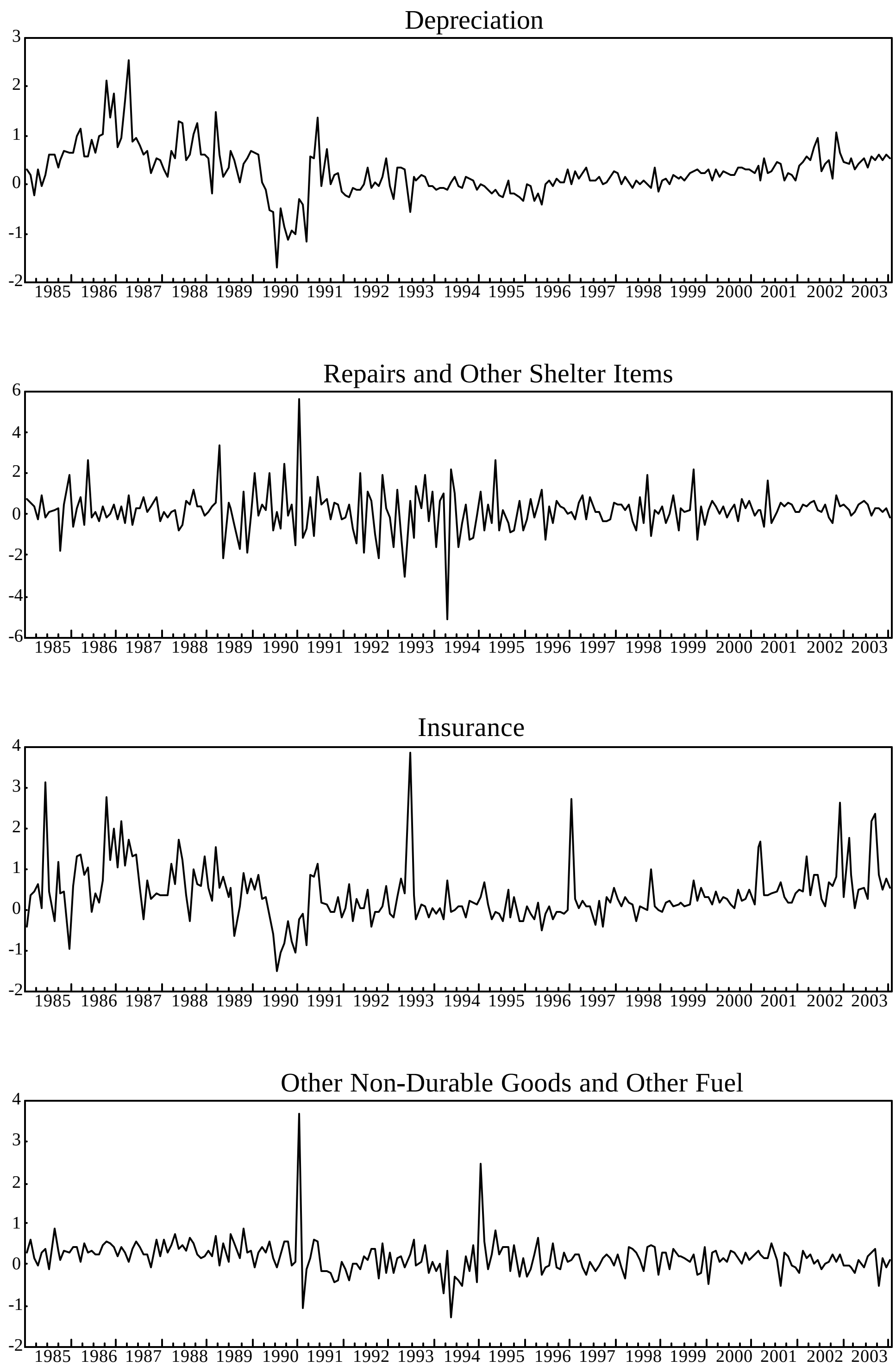
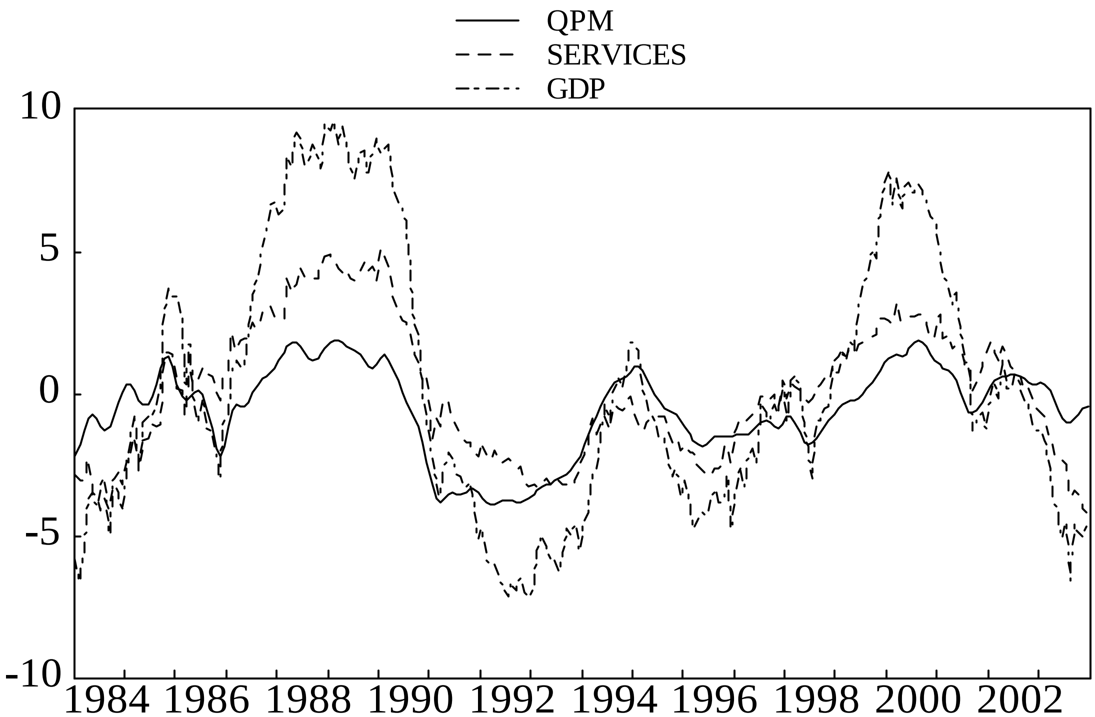


Figure 8: **Output-Gap Measures**



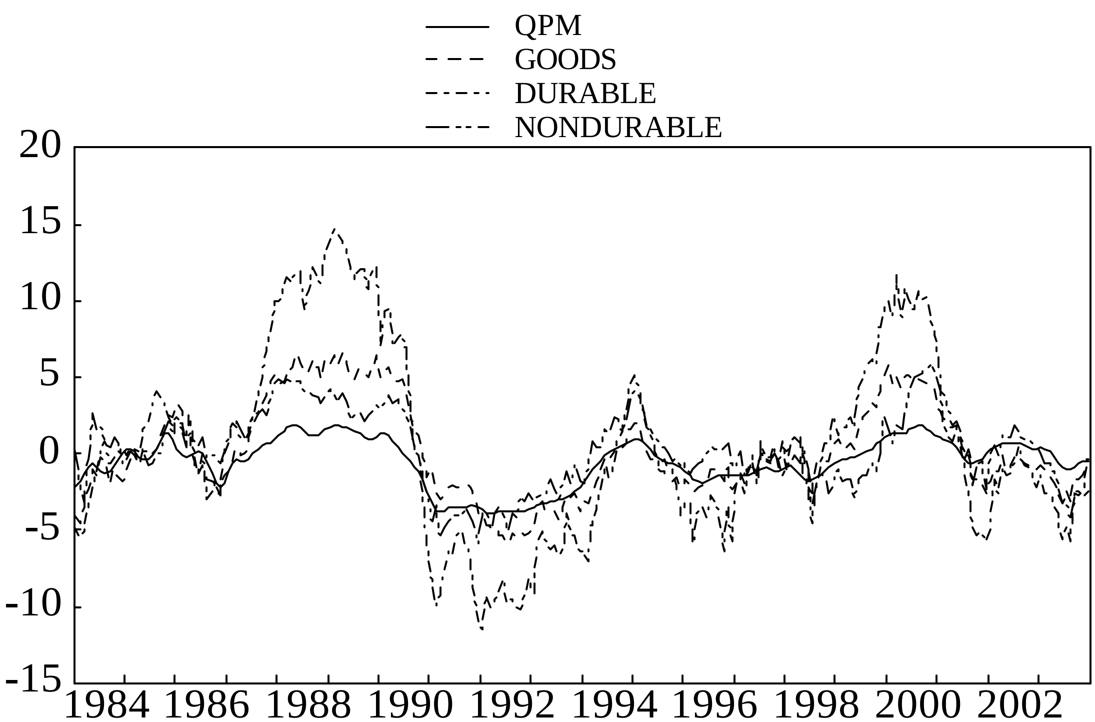
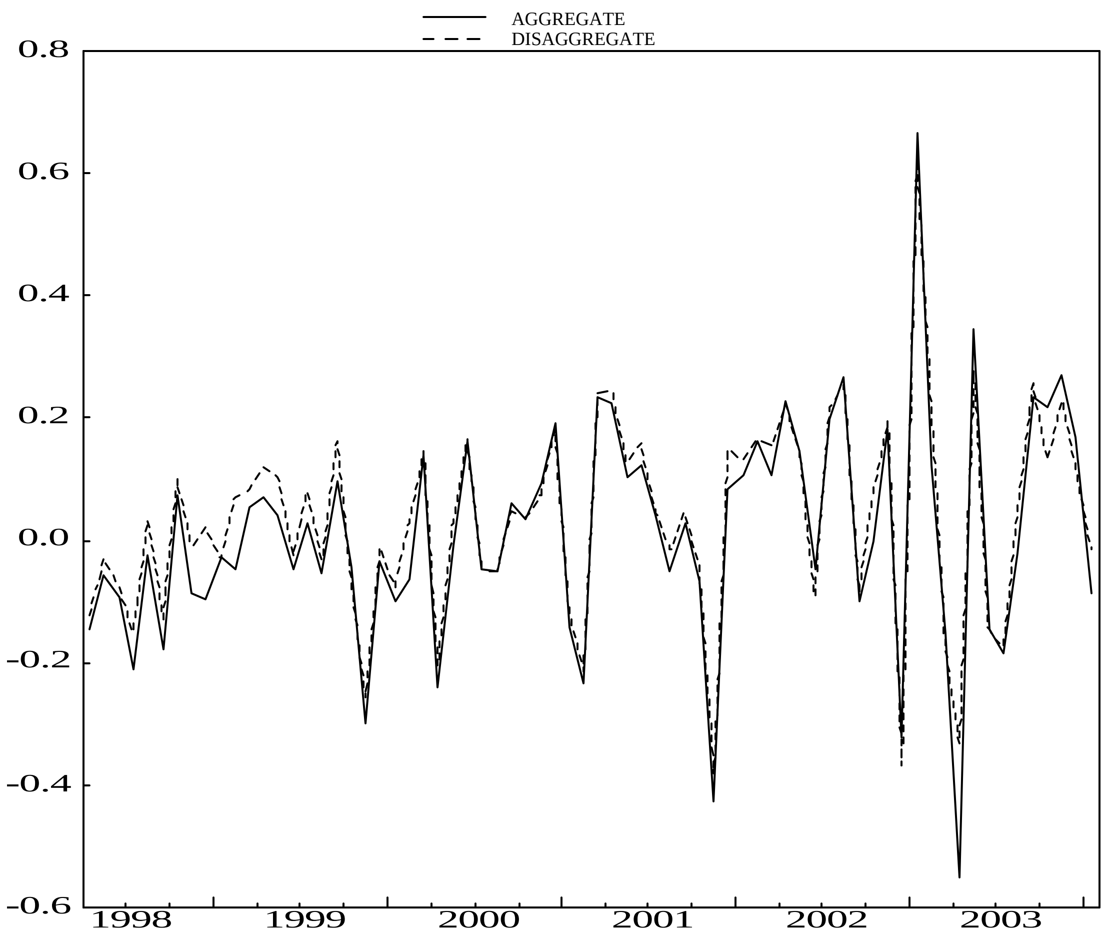


Figure 9: **1-Step-Ahead Forecast Error**



Appendix: Definitions and Sources

Table A1: Inflation Series Definitions

Mnemonics	Cansim Reference	Output-Gap Measure*	Weight**
Durable	v735590	2	0.176
Semi-Durable	v735591	2	0.083
Non-Durable Excluding Food, Energy, and Tobacco: *Non-Durable-X*	v735594, v735583	3	0.068
Food Excluding Fruits and Vegetables: *Food-X*	v735320, v735356, v735366	3	0.172
Electricity	v735409	1	0.026
Services Excluding Intercity Transportation and Food Away From Home: *Services-X*	v735408, v735396, v735597 v735515, v735392	4	0.272
Shelter Excluding Mortgage Interest Cost: *Shelter-X*	v735396, v735408, v735402	2	0.199
Other Food	v735321, v735356, v735366	3	0.110
Food Away From Home	v735392	4	0.062
Services Excluding Food, Communication, and Transportation: *Services-XFCT*	v735598, v735592, v735415 v735575, v735558, v735506	1	0.182
Automobile Insurance	v735506	4	0.033
Communication	v735415	4	0.033
Local Transportation	v735512	4	0.007
Alcohol in Restaurants	v735575	4	0.008
Hotel	v735558	4	0.010
Rent	v735397	4	0.073
Property Tax	v735404	1	0.038
Depreciation	v735403	1	0.037
Repairs and Other Shelter Items	v735406, v735407	2	0.035

*1 = *Total*, 2 = *Durable*, 3 = *Non-Durable*, 4 = *Services*.

**2003 basket definition.

(continued)

Table A1 (concluded)

Mnemonics	Cansim Reference	Output-Gap Measure*	Weight**
Home Insurance	v735405	2	0.012
Durable Ex. Automobiles	v735590,v735497	2	0.089
Automobiles	v735497	2	0.087
Alcohol	v735579	3	0.014
Other Non-Dur. +other fuels	v735594, v735579, v735589 v735548	3	0.058
Core	v735600	1	1.00

*1 = *Total*, 2 = *Durable*, 3 = *Non-Durable*, 4 = *Services*.

**2003 basket definition.

Table A2: Data Sources for the Exogenous Variables

Mnemonics	Cansim Reference
Durable Manufacturing Output: *Durable*	v2044345, v14182617
Non-Durable Manufacturing Output: *Non-Dur*	v2044344, v14182616
Goods-producing industries	v2044341
Business Sector Services	v2044337, v14182622
Business Sector Goods	v2044336, v14182621
Canada-U.S. (Noon Spot) Exchange Rate: E_t	v121716
GDP Deflator for Canada: p_t	v1997756
GDP Deflator for the U.S.: p_t^{US}	GDPDEF*

*GDPDEF is the series ID from the St. Louis FED FRED II Database.

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