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US Newsprint Demand Forecasts to 2020

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Contents

Abstract

The purpose of this study is to provide projections of newsprint demand for the United States (US) up to 2020. Three different approaches were used to compute the projections. First, various specifications of the standard model used in forest product demand literature, which we call the *classical model*, were estimated using annual data from 1971–2000. The results indicated that structural change in the newsprint consumption pattern took place at the end of the 1980s. The classical model fails to explain and forecast the structural change. It appears that changes related to the development of consumers' preferences and information technology (IT) may have caused the break down of the widely accepted positive relationship between the gross domestic product (GDP) and newsprint demand. These observations motivated the formulation of alternative models. Thus, a *Bayesian* model that allows industry experts' prior knowledge about the future demand for newsprint to be included in the projections was estimated. Also, an *ad hoc* model, in which newsprint demand is a function of changes in newspaper circulation, was used to compute projections. Finally, the forecasts of these models are evaluated along with some of the existing projections. Besides providing an outlook for US newsprint demand, the study contributes to the existing literature of long-term forest product demand by raising some methodological questions and by applying new models to compute projections. Contrary to some recent projections (e.g., FAO), the results indicate that US newsprint demand is likely to decline in the long run.

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US Newsprint Demand Forecasts to 2020

Lauri Hetemäki and Michael Obersteiner

1 Introduction

The subject of newsprint demand has a long tradition in forest products literature. According to Buongiorno (1996), the first study using econometric methods to analyze forest product markets was a study by Pringle (1954), in which he analyzed newsprint demand in the United States (US). Since Pringle's study, a large number of studies have been published on this topic. In addition, some organizations, such as the Food and Agriculture Organization of the United Nations (FAO) and the US Forest Service, regularly produces (roughly every 5 years) long-term forest products projections, which also include projections for US newsprint consumption. The purpose of these projections is, among others, to provide background information for policymaking concerning the forest sector. The most recent FAO study was published in 1999 and the US Forest Service study in 2001 (FAO, 1999a; Haynes, 2001).

The US newsprint market is particularly interesting to study due to its global significance and the methodological challenges it raises. It is the world's largest newsprint market, being slightly larger than the whole European market, and consuming about one third of the world's total production of newsprint. Roughly about half of this consumption is based on imported newsprint (mainly from Canada). It is clear that changes in the US market will also have important implications to world newsprint markets. Furthermore, the US newsprint market turns out to be a challenging and topical market to study from the methodological perspective. It appears that since the end of the 1980s, structural change has taken place in newsprint consumption in the US, which the conventional forest products demand studies fail to explain and forecast. In particular, the historical relationship between newsprint consumption and economic activity (GDP) seems to have changed in recent years in the US. Therefore, there is also a need to reassess the performance of the models used to forecast newsprint demand.

In this study, the long-term US newsprint forecasts are computed using three different methods. First, various specifications of a model which has dominated forest product demand literature for decades and which we name the "classical model" are estimated. In the classical model, the economic activity variable (GDP) and the price of newsprint are assumed to be the determinants of newsprint demand. Secondly, a Bayesian variation of the classical model is estimated. This approach allows to include subjective prior information, such as industry experts' views, to the estimation and forecasting of newsprint demand. To our knowledge, Bayesian methods have not yet been applied to forest economics literature in this way. However, as recent studies show, Bayesian methods can be very useful for forecasting purposes and the approach has become increasingly popular in applied econometrics (e.g., West and Harrison, 1997; Pole *et al*., 1999; Bauwens *et al*., 1999). The third method used is an *ad hoc model,* which includes the changes in newspaper circulation as an explanatory variable, thus named as "newspaper circulation model". Although, this model is not derived from economic theory (like the classical model), it can be justified on the basis of pragmatic reasoning and prior data analysis.

The results indicate that the sign of elasticity in newsprint demand with respect to GDP may have turned from positive to negative. Moreover, the GDP parameter is no longer statistically significant when a post-1987 sample is used for the estimation. Also, the newsprint price variable does not appear to contain significant explanatory power, if post-1987 data is used. Finally, the overall conclusion from the various projections is that the US newsprint demand is likely to decline in the next 20 years.

This paper is organized as follows. Section 2 provides the background for US newsprint demand projections and discusses some of the existing studies; Section 3 presents the theoretical and empirical methodology of the different approaches used in the present study; Section 4 describes the data; Section 5 reports the empirical results; and finally in Section 6 some conclusions and general remarks are provided.

2 Background

The long-term projections of the future consumption of forest products have significant practical relevance, since they are likely to influence government policymaking and private decision-making concerning the forest sector. Indeed, in the US the Forest and Rangeland Renewable Resources Planning Act of 1974 (RPA) actually requires the Secretary of Agriculture to periodically conduct assessments of the nation's renewable resources and their future development. In order to accomplish this objective, the US Forest Service produces so-called RPA Timber Assessment studies, which also include long-term projections for forest product consumption. These types of interests in the US and other countries sparked significant efforts in the late 1970s to build large scale and more sophisticated models for forest products projections and forest policy analysis. The most well known outcomes of these efforts are the TAMM model (Adams and Haynes, 1980), the GTM model (Kallio *et al*., 1987), and the PELPS model (Zhang *et al*., 1993).[1] These studies, along with the Solberg and Moiseyev (1997) study that surveys the European forest products modeling literature, give a good picture of the state-of-the-art in long-term forest products forecasting.

FAO has been publishing long-term projections since the beginning of the 1960s, the most recent being the FAO (1999a) outlook study. This report, which is based on the PELPS model, provides projections for global forest products consumption, production, trade, and prices up to 2010.[2] The most recent RPA Timber Assessment (Haynes, 2001)

[1] For a discussion of the projections and the methods see, e.g., Buongiorno (1977; 1996), Baudin and Brooks (1995), and FAO (1999b).
[2] Although FAO (1999a, b) calls its projection model the Global Forest Products Model (GFPM), its underlying principles are the same as the PELPS model (Zhang *et al*., 1993).

study provides an outlook of the timber situation in the US from 1996 to 2050. Both of these studies also include long-term projections for US newsprint demand. The FAO (1999a, b) projections are based on an empirical model, in which the demand for forest products are determined by economic growth (GDP), real prices of forest products, and lagged demand. This type of model has been used for decades in forest product demand literature and could thus be called “a classical model”. Because FAO (1999a) produces projections for a large number of countries and many product types, for simplicity the demand equations are estimated for three groups of countries, rather than for each single country. Thus, the model used to project demand for US newsprint is estimated by using annual data for 26 high-income countries from 1965 to 1994. The results for the estimated parameters are shown below:

$$\textit{News. cons.} = -0.02\ (\textit{news. price}) + 0.45\ (\textit{GDP}) + 0.46\ (\textit{lag demand}_{t-1})$$

The equation has a good fit; it explains 98% of the historical variations in newsprint consumption. The long-run price and income elasticities derived from the above equation are -0.03 and +0.82, respectively. These are in accordance with earlier elasticity results obtained in the literature (see review in Simangunsong and Buongiorno, 2001). On the basis of these findings, the FAO model could be regarded as a reasonable projection model. Moreover, the strength of this model is its the theoretical basis and simplicity. From Figure 1, one can observe that the model projects a steadily increasing demand for newsprint in the US during 1995–2010. In fact, the future trend follows more or less the historical trend.

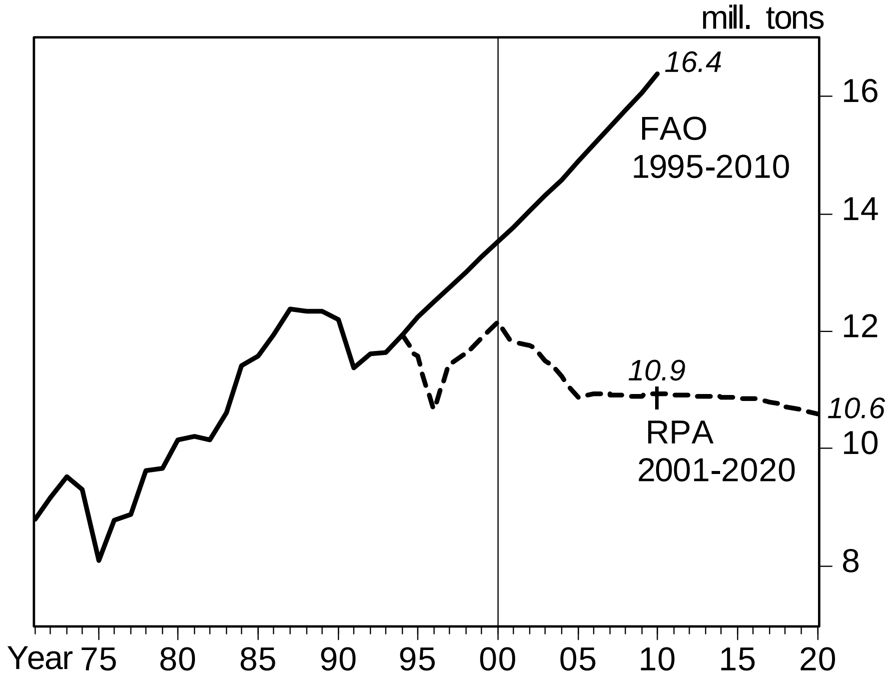

Figure 1: US newsprint consumption projections by FAO (1995–2010) and RPA (2001–2020).

It is also interesting to analyze in more detail the RPA model (Haynes, 2001) — it is the most up-to-date model and projection for US newsprint consumption in the literature. It can be regarded as a classical model, but with some novel features. It was originally formulated and estimated by Zhang and Buongiorno (1997) using annual data for 1960 to 1991. The RPA demand equation, which is derived from a two-stage Almost Ideal Demand System (AIDS), and the estimated values of the parameters used for computing the US newsprint projections (up to 2050) are shown below:

News. cons. = -0.22 (news. price) + 1.23 (GDP pc) + 1.0 (population) – 0.02 (technological change) – 0.95 (print media price) + 0.28 (capital price) – 0.07 (TVs/radios price) – 0.06 (computer price) + 0.1 (demand calibration dummy).

Besides including the classical explanatory variables (GDP per capita, newsprint price, population), the model has in addition four price variables and two dummy variables. Without going into details, the print media price index measures the impact of changes in the prices of printed materials, which will affect the printing and publishing industry and thus, in turn, newsprint demand. TV, radio, and computer prices reflect the possible substitution impacts of electronic media. The price of capital enters the equation due to the technical structure of the AIDS system. In the RPA equation, the estimated income and price elasticity parameters have the same signs as the FAO equation, but the absolute values are greater in the RPA equation.

RPA introduces the *demand dummy calibration variable* in order to make small adjustments to demand growth in the historical period of the model (1986–2000) so that the model is able to track actual historical demand quantities precisely. In addition, the dummy variable is used to dampen newsprint demand in the first few years of the projection period (beyond 2000) to reflect the current recession in the US economy and reduced newsprint demand. Furthermore, in the long run (after 2020), the dummy reflects assumed gradual substitution of newsprint by electronic media (reducing the rate of change in newsprint consumption to 70% of that which would otherwise have been predicted by the econometric formula). In the forecast period, population and GDP per capita are projected to increase along their historical trends. Relative prices of capital, printed material, and TVs/radios are assumed to increase modestly in the future while the price of computers is assumed to decrease over time.

Figure 1 shows that the RPA model projections are very different from FAO. In brief, the FAO projection reflects the increasing trend of pre-1987 data, whereas the RPA projection reflects the stagnating post-1987 trend. The difference between the two projections in 2010 is 5.5 million tons, which is equal to the annual production of roughly 16 modern newsprint mills (the total US production of newsprint in 2000 was 6.7 million tons). Both from the methodological and practical policy perspectives, it would be important to try to resolve which of the forecasts, if either, is the more plausible.

The apparent structural change in the newsprint demand pattern after 1987, indicated by Figure 1, suggest that one should study in more detail the applicability of the classical newsprint demand models to compute future long-term forecasts for US newsprint consumption. The classical model implicitly assumes that the structure and behavior of the forest product markets remains the same as in the past. In particular, the projections are very sensitive to the assumptions concerning GDP growth. Besides the importance of being able to accurately forecast the future GDP growth rate, it is important that the relationship between economic activity and demand for forest products remains stable. For the US, however, the relationship between newsprint consumption and GDP growth appears to have changed recently (see Section 5.1).

The RPA model acknowledges the recent structural changes and introduces dummy variables and the impact of electronic media to try to capture these changes to projections. The model implies that the relative prices between newsprint and electronic media are important determinants of newsprint demand. However, the underlying structure of the model is still the classical type, with GDP and the newsprint price variable playing an important role. Moreover, the dummy variables do not explain why the structural changes have taken place.

In summary, the results from the literature and the data indicate that it is necessary to analyze in more detail the apparent structural change in US newsprint demand, and the ability of the conventional models to explain the more recent data. Also, there seems to be a need to experiment with new types of models that would reflect the recent changes in consumers' media behavior, and could be used for long-term forecasting purposes.

3 Empirical Models

In this Section, the empirical models used to project newsprint demand in the US from 2001 to 2020 are presented. First, the "classical" model commonly used in forest economics literature is presented. Then the Bayesian approach is described, and finally the so-called "newspaper circulation model" is outlined.

3.1 Classical Approach

The basic structure of the econometric models used to project forest products demand has not changed significantly over time (see, e.g., McKillop, 1967; Kallio *et al*., 1987; Solberg and Moiseyev, 1997; Simangunsong and Buongiorno, 2001). Typically, the theoretical background of the models is production theory, according to which the forest product enters as an intermediate input in the manufacturing production function along with other inputs. Assuming a behavioral hypothesis, e.g., cost minimization, allows one to formulate an optimization problem from which the demand for the forest product can be derived. Typically, this setting produces a demand function, such as the one in the Global Forest Products Model (GFPM) (FAO, 1999a, b) and in Simangunsong and Buongiorno (2001), and expressed as equation (3.1):

$$D_{ik} = a_{ik} P_{ik}^{\sigma_{ik}} X_{ik}^{a_{\sigma_{ik}}} D_{ik,-1}^{\eta_{ik}}, \tag{3.1}$$

where D_{ik} is the demand in the ith country for commodity k, D_{-1} is demand in the previous year, P is the price of the commodity, X is gross domestic product, and σ, α, η

are the elasticities with respect to price, GDP, and past demand. For example, in the present case, i denotes the US and k denotes newsprint. The empirical model corresponding to equation (3.1), after logarithmic transformation and using the empirical data corresponding to the theoretical variables, can be written as:

$$\ln(d_{news,t}) = a_0 + \beta_1 \ln(p_{news,t}) + \beta_2 \ln(GDP_{USA,t}) + \beta_3 \ln(d_{news,t-1}) + \varepsilon_t \,, \tag{3.2}$$

where $d_{news,t}$ is the quantity of newsprint consumption in the US, $p_{news,t}$ is the real price of newsprint, $GDP_{USA,t}$ is the real gross domestic product in the US, $d_{news,t-1}$ is a lagged dependent variable measuring the possibility that in the short-run demand may adjust only partially, ε_t is the error term, and t is a subscript denoting the time period. Since the variables are in logarithmic form, the β-parameters can be interpreted directly as elasticities. Typically, the studies assume that the signs of the elasticities are known *a priori*. For example, Simangunsong and Buongiorno (2001:161) state that on the basis of the universality of economic laws of demand *"one would expect the price elasticity of demand to be non-positive and the GDP elasticity to be non-negative"*. In order to guarantee that the elasticities get correct signs and magnitudes, they can be restricted or directed in empirical estimation to fulfill this objective. Indeed, in Simangunsong and Buongiorno (2001) the so-called Stein-rule shrinkage estimator is used for this purpose.

In the present study, various specifications of equation (3.2) are used to estimate the demand for US newsprint demand and to compute long-term forecasts. However, in the estimation process, the signs or absolute values of the elasticities are not restricted. Also, the performance of the model is analyzed by estimating it for different data samples, and by formally testing whether structural change has taken place.

3.2 Bayesian Model

The motivation for using the Bayesian model is the acknowledgement that besides the historical time series data, there can be other information that is helpful in making long-term projections. For example, forest industry experts may have reasonable and useful views about future forest products market developments. Through their experience and knowledge about the industry, technology, and markets experts may have information that can help to project future newsprint consumption patterns. Therefore, by incorporating subjective expert views, one may be able to improve on the information set on which the "classical" projections are based. The Bayesian approach provides one possible method to coherently incorporate this type of information into econometric forecasting models.

Bayesian methods have become increasingly popular in empirical applications in recent decade (see, e.g., Bauwens *et al*., 1999; West and Harrison, 1997).[3] Indeed, current the literature is so large that one can identify many different methods within the Bayesian approach. However, to our knowledge, the genuine Bayesian estimation with informed

[3]Important factors behind this popularity are the increasing computer capacity and availability of software packages for Bayesian estimation.

priors has not been previously applied in forest products demand literature.[4] A number of Bayesian textbooks exist that explain the principles and differences of this approach relative to the frequentist statistical methods (e.g., Pole *et al*., 1999; West and Harrison, 1997). Here, only a brief description of one particular Bayesian method and the motivation of using it to forecast long-run newsprint demand in the US are given.

The starting point of our Bayesian framework is the above classical demand model. However, the Bayesian model allows the industry experts' knowledge about the relationship between newsprint consumption and GDP growth to be incorporated in the estimation. For example, if the industry experts believe that GDP growth does not have an impact on newsprint demand in the future, one could reset the mean value of the prior distribution of GDP accordingly. Notationally, this can be expressed as moving from the classical model or pure model based prior $p(GDP_t|D_{t-1})$ to the Bayesian post-intervention prior $p(GDP_t|D_{t-1}, I_t)$, where I_t denotes the external information available from the experts at time *t*. I_t is called the prior information set and hereafter prior. The prior of GDP is then combined with the information from observed data that is quantified probabilistically by the likelihood function. The resulting synthesis of prior and likelihood information is the posterior distribution of information. In other words, the posterior distribution quantifies the collection of the industry experts' beliefs about the GDP and the information gained from inference using historical data.

The Bayesian framework in the present study is also based on the classical equation [equation (3.2)] but, unlike the "frequentist approach", the Bayesian model assumes *a prior distribution* for the GDP parameter (β_2). In this case, we used an informed prior for the estimation of β_2, while all of the other parameters in equation (3.2) were derived using a so-called diffuse prior adding no additional information to the parameter estimation other than historical data.

Obviously, the choice of a particular prior distribution for the GDP parameter can have substantial impact on *posterior* model probabilities and the results. The technical details on how the industry experts' "informed prior information" is incorporated in our Bayesian econometric model is described in Appendix I. Here, we only present the general idea.

The Bayesian parameters (posteriori) were estimated using the Normal-Gamma regression model. The Normal-Gamma model is a mixed distribution model where prior information is assumed to be distributed according to a gamma distribution, which is combined with normally distributed parameters from time-series data. The estimation method used is ordinary least squares (OLS), as described in equations (A6) and (A7) in Appendix I. As prior information, we used information that was derived from US newsprint consumption scenarios that three industry experts produced. Scenarios for newsprint consumption were established by the industry experts up to 2013 in 5-year intervals from 1998 onward. The methodology is briefly described in Section 4 and

[4]Simangunsong and Buongiorno (2001) use an "iterative empirical Bayesian estimator", which is basically a Stein-rule shrinkage estimator in the dynamic setting. The approach is qualitatively different from the Bayesian method used here.

more detail is given in Obersteiner and Nilsson (2000). From the historical time series data and the information provided by the experts, a panel data set was constructed and used to estimate equation 3.2. For the parameter estimation of the 'expert model' we used the OLS fixed effects estimator. Finally, for the computation of the Normal-Gamma regression model, the newsprint consumption data for the period 1987–2000 was used.

3.3 Newspaper Circulation Model

The data on US newsprint consumption, GDP, and newsprint price indicate that the historical relationship between these variables appears to have changed after 1987 (see Section 5 and Figure 4 for more details). Therefore, it is of interest to analyze whether other variables exist that could explain the recent changes in the newsprint market and contain important "causal" relationship to newsprint demand. Here, we experiment with a model that uses changes in newspaper circulation as an explanatory variable, which we therefore name "the newsprint circulation model".

Unlike the classical model, our newsprint circulation model is not derived from economic theory, but it is an *ad hoc* type of model. However, pragmatic reasoning and statistical analysis of the underlying data suggest that changes in newspaper circulation may be an important determinant of newsprint consumption. It appears logical to think, that the more (less) people read newspapers, and thus the higher (lower) the newspaper circulation is, the more (less) there is also demand for newsprint. In Figure 2 the newspaper circulation in the US, along with population development, are shown for the period 1940–2000. The figure shows that after 1980 the volume of daily newspaper circulation has stagnated and from 1987 onwards has actually started to decline, despite the continued increase in the population. Thus, in the US people read fewer newspapers than previously. Furthermore, from Figure 3, which shows the annual changes in newspaper circulation and the newsprint consumption for 1987–2000, it is evident that the two series follow a very similar pattern. This is what we would expect since, *ceteris paribus*, the smaller the circulation the less demand there is for newsprint.[5] Finally, we analyzed the "causality relationship" between changes in newspaper circulation and newsprint consumption using the *Granger causality test*. Granger causality measures precedence and information content between two variables, but does not by itself indicate causality in the more common use of the term. Therefore, the test does not *necessarily* imply that newsprint consumption is the effect or the result of newspaper circulation, although it could be. Bearing this in mind, the test results indicated that newspaper consumption is "Granger-caused" by newspaper circulation, but not vice versa.[6]

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[5]From analyzing the simple correlation coefficients and running the Granger causality tests for various specifications of the newspaper circulation variable, the results indicated that it is indeed the *change* in newspaper circulation rather than its *level* that is more closely related to newsprint consumption.

[6]The Granger causality test equation included lagged (one and two periods) newsprint consumption and the changes of newsprint circulation variable. The newsprint circulation turned out to be a statistically significant determinant of the newsprint consumption, but not vice versa. Thus, there is no two-way Granger causality present in these series.

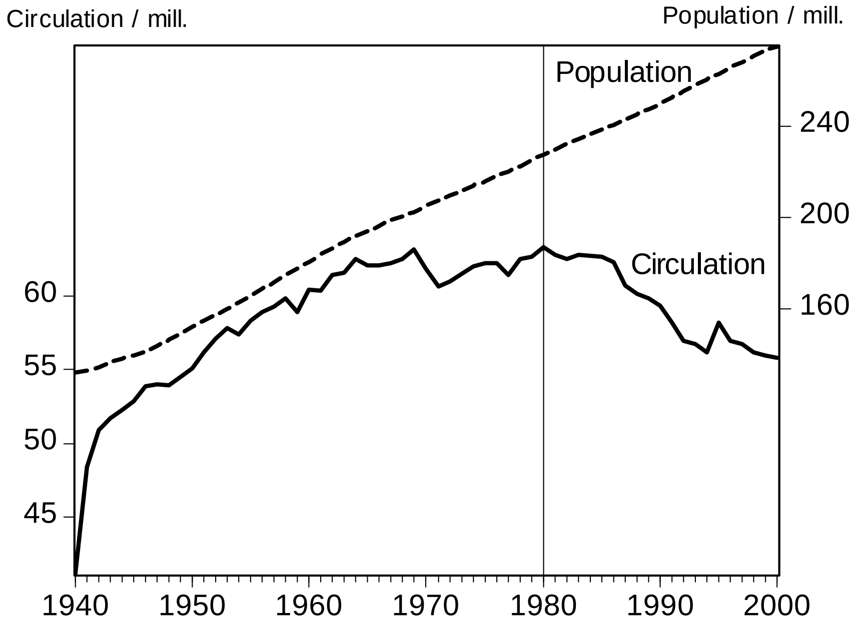

Figure 2: Newspaper circulation volumes and population in the US, 1940–2000.

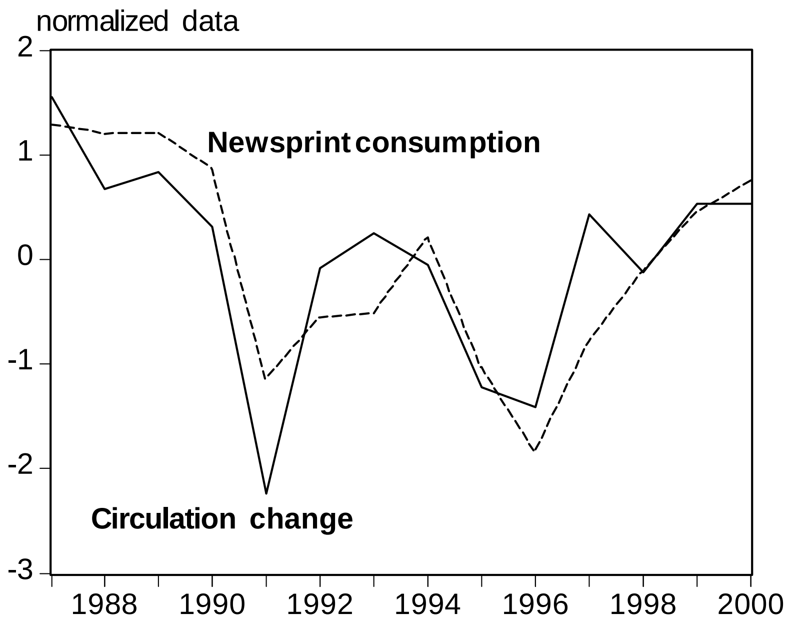

Figure 3: Newsprint consumption and changes in newspaper circulation in the US, 1987–2000 (data values normalized around zero).

On the basis of the above reasoning, the following model to forecast newsprint demand was formulated in logarithmic form:

$$\ln(d_{news,t}) = \gamma_0 + \gamma_1 \Delta \ln(circ_{news,t}) + \gamma_2 \ln(d_{news,t-1}) + \mu_t \qquad (3.3)$$

where $(d_{news,t})$ is the quantity of newsprint consumption in the US, $\Delta(circ_{news,t})$ is the change in the volume of newspaper circulation, $d_{news,t-1}$ is lagged dependent variable measuring the short-run dynamics in demand, μ_t is the error term, and t is a subscript denoting the time period. We would expect the γ_1-parameter to have a positive sign, since an increase in circulation should cause an increase in newsprint consumption.

4 The Data

The data used to estimate the different models consisted of 30 observations from 1971 to 2000, or its two sub-periods: 1971–1987 and 1987–2000. Because of the tendency for economic time series to exhibit variations that increase in mean and dispersion in proportion to the absolute level of the series, we follow the common practice and transform the data by taking logarithms prior to analysis. This transformation also allows us to interpret the estimated parameters as elasticities in the demand equations.

The *newsprint consumption* variable used refers to uncoated paper, unsized (or only slightly sized), containing at least 60% (percentage of fibrous content) mechanical wood pulp, usually weighing not less that 40 g/square meter and generally not more than 57 g/square meter of the type mainly used for printing newspapers. Most newsprint is used to print daily and weekly newspapers. The other major uses are inserts, flyers, newspaper supplements, and directories. The data for the years 1980–2000 is obtained from Newspaper Association of America (NAA). For the years 1971–1979, the FAO data for *apparent* newsprint consumption was used. Since the FAO figures are on average 4.9% higher than the figures reported by NAA, the observations for 1971–1979 were scaled down by this percentage. NAA data measures the actual consumption, whereas FAO data measures the apparent consumption, which includes the inventory. However, the qualitative results are not sensitive to whether one uses the NAA or FAO data. [Sources: Newspaper Association of America (primary sources: Canadian Pulp and Paper Products Council, US Department of Commerce); FAOSTAT online database.]

Newsprint price is the transaction price of yearly averages for 48.8 gram standard newsprint (Eastern US prices). The nominal price is transferred to real price by deflating it using an implicit price deflator for personal consumption expenditures. For the years 2000 to 2020, it is assumed that the price of newsprint stays at its 1999 level. [Sources: Newspaper Association of America (primary source: Resource Information Systems Inc; US Bureau of Economic Analysis (http://www.bea.doc.gov).]

The *US real gross domestic product* (GDP) data (both in per capita and at the country level) refers to GDP in 1996 prices (US$). The data was obtained from the US Bureau of Economic Analysis, Department of Commerce. It is assumed that real GDP will grow by 2.40% annually between 2001 and 2020. This is the same assumption that FAO (1999a) uses for its projections for the US from 1995 to 2010. The population data and projections for 2020 refer to mid-year population and were obtained from the US Census Bureau.

The US daily *newspaper circulation* refers to volume number in millions. [Source: Newspaper Association of America (http://www.naa.org/info/facts01/index.html).]

For the derivation of the *Bayesian prior*, the scenario plots constructed by a group of research and development (R&D) managers of the paper industry were used. The experts participated in an online course on 'Managing Technology for Value Delivery' at the University of British Columbia (Procter, 2000), in which scenarios for future US newsprint demand were formulated. The expert group used a methodology for scenario plotting developed by Obersteiner and Nilsson (2000). According to this methodology, course participants were asked to give quantitative input for about three main force factors determining the development of the US newsprint market. These force factors were: (1) economic and life style development, (2) substitution of newspaper content between paper and electronic media, and (3) newsprint intensity of newspaper making (basically future changes in the weight and size of the average newspaper). These factors were allowed to vary for different population cohorts, distinguished by gender, age, and education, in order to model demographic shifts due to ageing and education triggered changes in the consumption pattern. Population trajectories were computed by IIASA's Population Project (Lutz and Goujon, 2001) and were, thus, exogenous information to the experts. After the initial scenarios were formulated, they were iteratively discussed, commented and improved by course participants.

There were only three experts that provided full scenarios during the course. It is clear that the number of experts is very small, and therefore the results may not be generalized to reflect the view of the whole industry, but rather represents a case study. However, from the Bayesian methodological point of view, the small number of experts is not a critical issue for being able to use the method.

5 Empirical Results

5.1 Time Series Properties

Before the actual estimation of the different models, the time series properties of the underlying data were analyzed using graphs, autocorrelation functions, Augmented Dickey-Fuller (ADF) and Philips-Perron (PP) tests, and various cointegration tests. The results indicated that newsprint consumption, GDP, and newsprint price series are non-stationary series (the results are shown in Appendix II).[7] The various cointegration test results pointed to the possibility of either zero or one cointegration relationship between these variables. The newspaper circulation change series is on the border of being a I(0)

[7]The ADF tests were run both with and without the deterministic trend. According to the ADF test results, newsprint consumption, GDP, and price series can be regarded as I(1)-series at the 5% significance level.

or I(1) series — the null hypothesis of non-stationarity can almost be rejected at the 5% level. The correlogram and the graph of the series suggest that it is a stationary series.

What implications should the above unit root and cointegration test results have to modeling, estimation, and interpretation of the results? Clearly, when there are non-stationary variables in the models, particular concern should be attached to the possibility of spurious regressions and biases in standard errors. However, from the model strategy perspective, the results do not give unambiguous guidance. For example, in a recent survey, Allen and Fields (1999) conclude that the econometric literature gives no generally accepted principles on how one should utilize the unit root and cointegration test results for model strategy. In the present study, this question is made even more difficult due to the small sample, which casts doubt as to the robustness of unit root and cointegration tests, and also makes it difficult to estimate equations with large number of variables or systems models (in some specifications only 14 observations were used, see below). In the present study, a strategy of trying to keep the model specifications as simple as possible, given that the specifications were still statistically robust on basis of a number of different miss-specification tests, was chosen.

The initial analysis of the graphs and descriptive statistics of the data indicated that it would be informative to estimate the models for various sample periods. Figure 4 shows the newsprint consumption, real price, and real GDP series for the period 1971–2000 (the series are in logarithms and normalized around 0). The trend in newsprint consumption increased during 1971–1987, except for the periods relating to the oil crises (1973–1975 and 1980–1982). After 1987, newsprint consumption started to stagnate, indicating a structural change in the pattern. Figure 4 also shows that the reason for stagnating newsprint consumption is probably not related to GDP or newsprint price, since real GDP has continued to increase along its long-run trend and real newsprint price has continued its declining trend.[8] These changing patterns between the series can also be observed in the simple correlation coefficients shown in Table 1. For the sample period, 1971–1987, the correlation coefficient between newsprint consumption and real GDP is positive and very high (0.91), while for the period 1987–2000 it is negative and markedly lower (-0.25). Similarly, major changes in the signs and absolute values of the correlation coefficients between newsprint consumption and price series, and between price series and GDP has taken place. However, when interpreting the latter correlation coefficients, one should be aware of the significant jump in the price series during 1995–1996.

In summary, the data analysis shows that the results are likely to be very sensitive to the particular sample period used for the estimation. This suggests that one should experiment with estimating the models for various time periods, instead of only using the whole sample period data.

[8]Also, the stagnation cannot be related to population growth, since it has also continued to increase along the long-run trend.

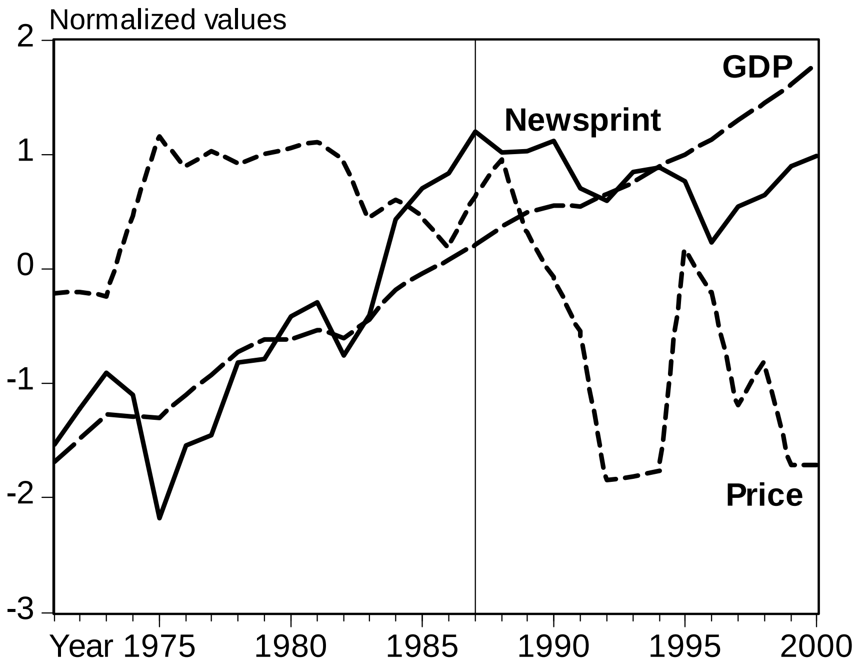

Figure 4: US newsprint consumption, real GDP, and real newsprint price, 1971–2000.

Table 1: Correlation coefficients.

	SAMPLE	LGDP	LPRICER
LNEWS	1971–2000	0.85	-0.48
	1971–1987	0.91	-0.09
	1987–2000	-0.25	0.29
LGDP	1971–2000		-0.65
	1971–1987		0.27
	1987–2000		-0.59

5.2 Classical Model

Due to the structural break in the data, estimations of the classical model were computed for the following three periods: 1971–2000, 1971–1987, and 1987–2000. The latter two sub-periods have very few observations (17 and 14, respectively) and the results should therefore be interpreted with caution. Still, the sub-period estimations are likely to produce more meaningful results than using the whole sample. Besides estimating the basic classical model for different observation periods, three different model specifications were also estimated. Because of possible simultaneity between the newsprint consumption and its price, a simple vector-autoregressive (VAR) systems model was also estimated. Moreover, a static version of the classical model was computed. Finally, a specification where the impact of population changes were incorporated by using the newsprint consumption per capita as an dependent variable and the GDP per capita as an explanatory variable was computed. Table 2 provides the summary of the estimation results.

Table 2: Estimation results.

MODEL ***estimated period***	**Constant**	**sr GDP**	**lr GDP**	**sr Price**	**lr Price**	**Lagged Demand**	**Δ Newsp. Circulat.**	$\bar{R}^2$	**B-G serial correlation 5% level**
1. Classical *1971–2000*	-0.09 (0.17)	0.08 (1.05)	0.33	-0.01 (0.17)	-0.05	0.77 (6.09)		0.87	No
2. Classical VAR *1971–2000*	-0.35 (0.70)	0.09 (1.22)	0.09	0.05 (0.80)	0.05	0.79 (6.02)		0.87	No
3. Classical *1971–1987*	3.07 (5.12)	0.70 (6.57)	0.84	-0.49 (4.79)	-0.58	0.16 (1.18)		0.95	No
4. Classical *1987–2000*	0.93 (0.80)	-0.01 (0.07)	-0.01	-0.02 (0.30)	-0.06	0.66 (2.01)		0.17	No
5. Classical Static *1971–2000*	-1.61 (2.41)		0.44 (7.18)		0.09 (0.91)			0.72	Yes
6. Classical Per Capita *1971–2000*	0.68 (0.71)	0.03 (1.20)	0.13	-0.01 (0.11)	-0.01	0.76 (6.15)		0.87	No
7. Bayesian Prior Panel *1989–2013*	1.10 (2.30)	-0.06 (2.22)		-0.54 (5.09)		1.14 (22.79)		0.98	No
8. Bayesian Posterior *1987–2000*	0.92 (0.46)	-0.02 (0.10)		-0.04 (0.24)		0.71 (1.17)			No
9. Newspaper Circulation *1987–2000*	1.25 (6.43)					0.51 (6.47)	3.11 (10.56)	0.92	No

Note: t-values are in parentheses.

In Table 2, the Models 1 to 6 show the results for various specifications of the classical frequentist models. For the dynamic specifications (i.e., models with lagged dependent variable) both the short-run (sr) and long-run (lr) GDP and price elasticities were computed. Also, the respective t-values are shown in parentheses, the adjusted coefficient of determination ($\bar{R}^2$), and the conclusions from the Breusch-Godfrey (B-G) LM test for second order serial correlation at the 5% significance level are shown (for a more detailed report of the estimation results, see Appendix III).[9]

[9]The assumption of OLS requires the error term to be normally distributed (if this does not hold, e.g., the *t*- and R^2-values may be biased). The Doornik-Hansen test results indicated that all the other models except Model 4 have non-normal residuals. Further analysis indicated that the reason for the non-normality is due to two outlier observations related to the oil crises. By including a dummy variable, which took value 1 in 1975 and 1982 and zero otherwise, resulted in normally distributed error terms in Models 1–3 and 5–6.

In analyzing how well the different specifications succeed in explaining the historical changes in newsprint consumption ($\bar{R}^2$ -statistics, t-values), Model 3 appears to best fit the data and Model 4 the worst. Thus, the classical model does not seem to be able to explain the changes in the US newsprint consumption during 1987–2000. This was also confirmed by a Chow breakpoint test, which tested whether the same classical newsprint demand model (Model 1) could be used to describe the data before and after 1987. The test results decisively rejected the null hypothesis of no structural change in the demand function. The structural change can also be observed from Figure 5, showing the cumulative sum of the recursive residuals (CUSUM) together with the 5% critical lines. If the equation (i.e., the parameters of the equation) remains constant, the CUSUM line will wander close to the zero mean value line. In the figure, after 1987 the CUSUM line starts to sharply diverge from the mean line, and in 1996 onwards falls below the 5% critical lines. Thus, the recursive residuals clearly indicate instability in the equation after 1987.

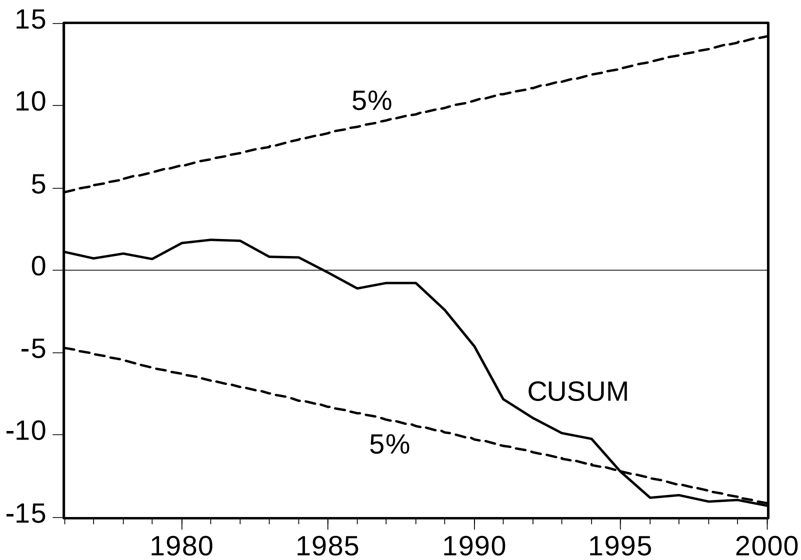

Figure 5: The cumulative sum of the recursive residuals (CUSUM) of Model 1.

The long-run elasticity estimates for Model 3 show that during the period 1971–1987 newsprint consumption is rather responsive to the changes in GDP and newsprint price (0.84 and -0.58, respectively). Indeed, the GDP elasticity is very close to the elasticity of 0.82 obtained by FAO (1999a) for the group of high-income countries (the price elasticity in the FAO study was -0.03). However, Table 2 shows that for the specifications, including the data up to 2000, the estimated GDP elasticity has a markedly lower absolute value. If the data sample consists only of post-1987 observations, the elasticity obtains a negative sign (Model 4). Figure 6 also illustrates these changes, where the recursive coefficient estimates for GDP are shown with two respective standard error bands. The GDP elasticity coefficient displays significant variation as more data is added to the estimating equation, indicating instability. At the beginning of the sample the absolute value is above 0.8, but after 1987 there is a sharp decline in the absolute value of the coefficient and it approaches zero when more recent data is used to estimate the coefficient.

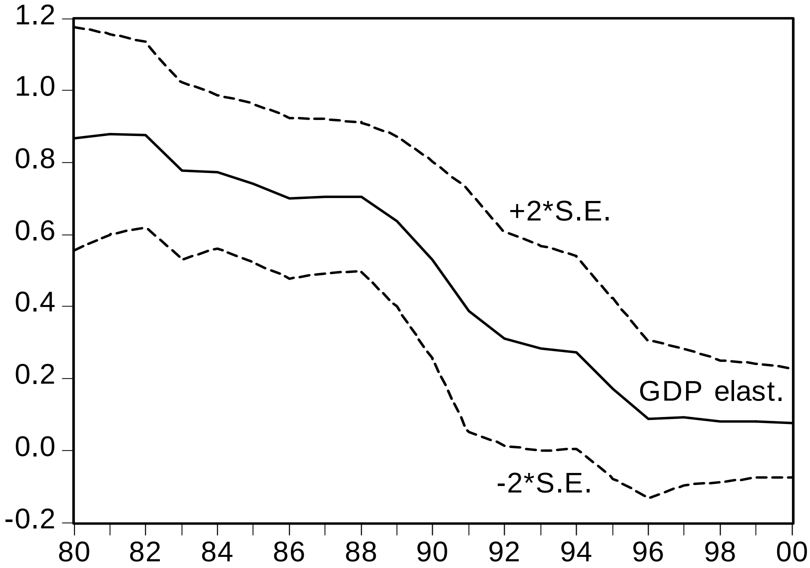

Figure 6: Recursive coefficient estimates for GDP.

The results in Table 2 show that the static specification (Model 5) has a problem with serial correlation, indicating that some dynamics is necessary. However, the absolute value of the GDP elasticity is of similar magnitude in the static and dynamic specifications. The per capita specification (Model 6) produces lower absolute values for GDP and price elasticities, but they are also statistically insignificant.

The above models were used for forecasting US newsprint demand up to 2020. Forecasts of the present study are *ex post dynamic* forecasts from the different specifications. Dynamic forecasts involve multi-step forecasts starting from the first period in the forecast sample (1988–2020 or 2001–2020). Unlike in static forecasts, the previous period error is not checked, nor are corrections for errors incorporated in subsequent forecasts.[10] Therefore, newsprint forecasts do not benefit from knowing the newsprint in the previous time period or knowing the previous forecast errors. For the values of the exogenous variables in the forecast horizon, the following assumptions were made. The real GDP is assumed to grow at the same rate as assumed in FAO (1999a), i.e., by 2.40% annually between 2001 and 2020 (the mean figure for 1971–2000 is 3.30%). For the newsprint price we assume that it stays at its 2000 level for 2001–2020.

[10]A *static forecast* produces a sequence of one-step-ahead forecasts, using actual rather than forecasted values for the lagged dependent variables.

The forecast results for 2010 and 2020 are shown in Table 3. First, the FAO (1999a) and RPA (Haynes, 2001) projections are shown.[11] FAO's projection is based on estimating a classical newsprint demand equation using data up to 1994 and making forecasts from 1995 to 2010. Model 3 is estimated using data from 1971–1987 and forecasts are for the period 1988–2020. All the other specifications provide forecasts from 2001 to 2020 (RPA actually provides projections up to 2050).

Table 3: Forecasts for US newsprint consumption (in millions metric tons).

MODEL	1994	2000	2010	2020
Actual values	*11.9*	*12.2*		
FAO (1999a)		13.5	16.4	
RPA (Haynes, 2001)			10.9	10.6
1. Classical 1971–2000			13.9	15.1
2. Classical VAR 1971–2000			13.3	14.3
3. Classical 1971–1987	18.0	21.8	26.8	32.7
4. Classical 1987–2000			11.9	11.8
5. Classical Static 1971–2000			14.4	15.9
6. Classical Per Capita 1971–2000			15.3	17.3
7. Bayesian Prior Panel 1989–2013			11.9	11.7
8. Bayesian Posterior 1987–2000			12.1	11.9
9. Newspaper Circulation 1987–2000			11.1	7.4

Model 3 (1971–1987) generates the highest forecasts and Model 4 (1987–2000) the lowest. Comparing the projections of Model 3 to actual data for 1988–2000, we can infer that Model 3 overestimates the actual figures in 2000 by roughly 80%. Similarly, the FAO (1999a) forecast overestimates the 2000 figure by 11%. The evolvement of the forecasts over time is also shown in Figure 7. It shows that Model 3 projects increasing consumption during 2000 to 2020, more or less along the pre-1987 historical trend. Model 1 projects slightly increasing consumption, whereas Model 4 takes the post-1987 structural change into account, and projects stagnating consumption.

In summary, the estimation results point consistently towards a historically important structural change in the US newsprint consumption after 1987. None of the different specifications of the classical model provided statistically satisfactory results for the data after 1987. Also, one implication of the results is that, for the newsprint demand in US, *the universality of economic laws of demand* that are interpreted to require non-negative GDP elasticity (cf. Simangunsong and Buongiorno, 2001), may not hold. Finally, the results clearly point towards a need to develop new models that are more capable in explaining the recent behavior of newsprint markets in the US.

[11]It should be noted that FAO provides three different projections: low, median, and high, depending on the particular assumptions imposed. The discussion in this study is based on FAO's (1999a) median scenario, which is considered to be the "most likely".

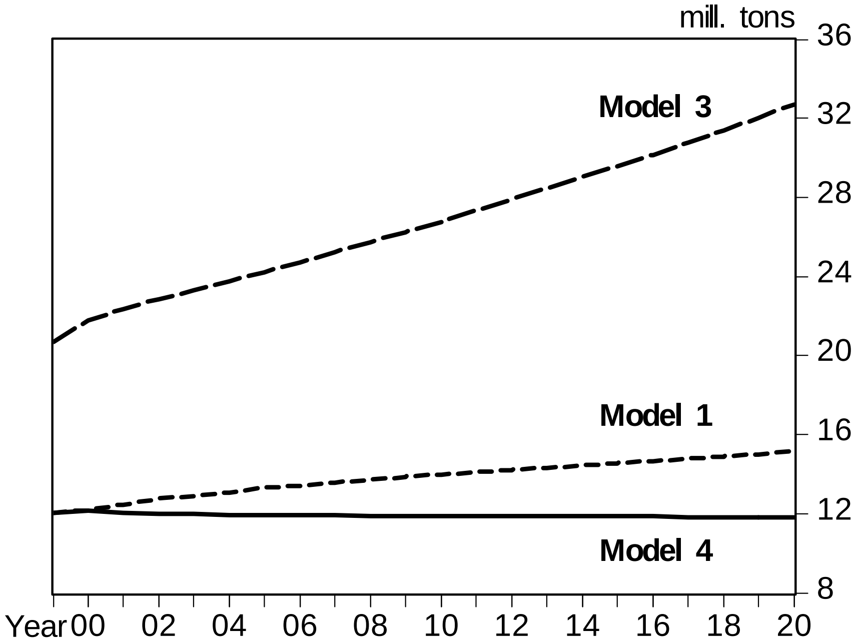

Figure 7: Forecasts from classical models, 2001–2020.

5.3 Bayesian Model

The Bayesian Prior model (Model 7) was estimated using the panel data set that was constructed from the information provided by the experts and, thus, reflects the 'consensus' of the industry experts. For the estimation of the Bayesian Posterior model (Model 8), we used the second moment of the GDP elasticity of the expert model as an informed prior. For the newsprint price and lagged demand parameters the so-called diffuse priors, which are technically equivalent to large second moments, were used. The use of diffuse priors is due to the fact that experts were not required to make specific assumptions on prices or lagged demand.[12]

The absolute values of the estimated parameters for Models 7 and 8 are very close (see Table 2). The GDP elasticity of the Bayesian Posteriori model is, at two decimal points, equal to the GDP elasticity of the expert model (Model 7). This is due to the prior high precision of the GDP elasticity from the experts. On the other hand, the values of the estimated parameters for newsprint price and lagged demand differ somewhat between Model 7 and Model 8. Figure 8 shows that the forecasts produced by Model 7 are only slightly lower than Model 8 projections. Moreover, the projections indicate a rather small decline over time in newsprint consumption — a drop of about 0.3 or 0.4 million ton in 20 years. Comparing the Bayesian estimation results to the classical model using the same sample observations (Model 4), it is interesting to note the similarity of the estimates and forecasts. Thus, in this study the use of expert information does not

[12] Due to this assumption the information contained in the second moments were not directly used as priors for H^*. Furthermore, official newsprint prices reflect only spot market fluctuations and exclude the large volumes traded on long-term contracts and are, thus, not fully informative.

change the projections due to the fact that the experts' views in the present case seem to reflect the implications of recent historical data. However, the projections would diverge if the experts' views would be different to the projections that are consistent with historical data.

In the present study, the Bayesian framework was used to set a prior distribution only for the GDP parameter. The natural extension of this approach would be to set a prior also for the newsprint price parameter. Furthermore, a key aspect of the model is the uncertainty related to the choice of the regressors, i.e., model uncertainty. Thus, we could also specify a prior distribution over the model space (Fernandez *et al.*, 2001). More importantly, due to the low explanatory power of the GDP and the price parameter in the US newsprint demand model, one should try to look for new variables also in the Bayesian setting that could better explain the recent newsprint consumption behavior.

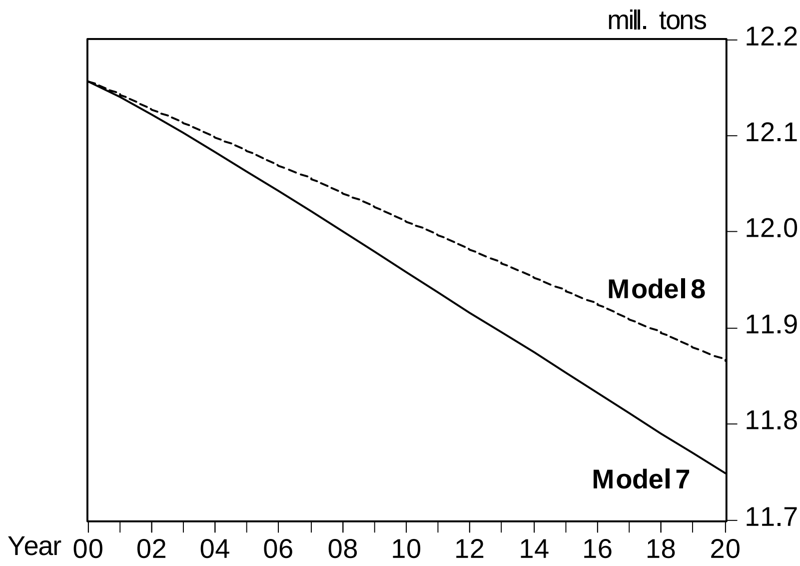

Figure 8: Forecasts from Bayesian models, 2001–2020.

5.4 Newspaper Circulation Model

The newspaper circulation model [equation (3.3)] was estimated using data for the period 1987–2000. The small sample restricted the number of variables that could be included in the model. Thus, besides the constant term and the newspaper circulation variable, only the lagged newsprint demand variable was included. The lagged dependent variable allowed some dynamics and increased the explanatory power of the model. The estimated parameters did not appear to suffer from multi-collinearity, since their absolute values changed only marginally depending on whether the estimated equation included only one of the explanatory variables or both.

The estimation results of equation 3.3 showed that the specification is acceptable using the conventional statistical criteria for autocorrelation, residual normality, stationary, heteroskedasticity, functional form misspecification, and explanatory power (detailed results shown in Appendix III). However, it should be borne in mind that the robustness of these results are subject to the problems related to the small sample. The absolute value of the changes in newspaper circulation parameter indicates that, *ceteris paribus*, a 1% increase in newspaper circulation would lead to a 3.1% increase in newsprint demand (see Table 2). Thus, newsprint demand appears to be very elastic with respect to circulation.

In order to be able to compute the conditional forecasts, assumptions about the development of newspaper circulation during 2001 to 2020 had to be made. These were based on recent data on newspaper circulation and households "consumption" of media, and on the findings of some recent US media studies (e.g., NAA, 2001; UCLA, 2001). Looking at historical development from 1987 onwards, when newspaper circulation started to decline, we observe that circulation declined on average by 0.48% annually during 1987–2000. However, the annual average rate of decline has accelerated somewhat, being 0.59% for the last five years. The declining interest in newspapers is apparent also in the data on media consumption of US households. Table 920 in the Statistical Abstracts of the United States (2000), shows how many hours households annually spend on different media. According to these statistics, households spent 10% less time reading newspapers in 2000 than in 1992, while at the same time increasing Internet consumption by 2050%. Although the relative change in Internet consumption is huge, its absolute significance is small due to the very low starting level. Nevertheless, the underlying tendency is declining newspaper consumption and simultaneous increase in Internet consumption. A similar pattern was found in a recent study by the North American Newspaper Association (NAA, 2001:4), which surveyed the media behavior of a nationally representative sample of 4003 adults, aged 18 and over. According to the study "*The first and perhaps most significant finding of the study is the decline in penetration of traditional media including newspapers, TV, and radio and the concurrent rise in the use of the Internet as a source of news and information*". The study also reports evidence that the two phenomena are connected, i.e., the increasing usage of the Internet accelerates the decline in newspaper readership. These findings are supported by other studies, such as the NAA (2001) and UCLA (2001) survey studies.[13]

In the newspaper circulation model, the above data and surveys were interpreted to imply an increasing rate of decline in newspaper circulation in the US during 2001 to 2020. In particular, we assumed that US newspaper circulation is declining by 1% annually during 2001–2005, by 2% annually during 2006–2010, by 4% annually during 2011–2015, and by 8% annually during 2016–2020. These numbers are *ad hoc*, and should not be taken as precise projections, but rather as one possible scenario for newspaper circulation development. More important than the absolute numbers is the general trend. The above numbers assume that no dramatic change is taking place and that the rate of circulation decline increases steadily. We regard the assumptions to be moderate rather than extreme.

[13] It may be noted, that newsprint consumption is stagnating also in Japan and in some European countries.

The dynamic forecasts of the newspaper circulation model based on the above assumptions are shown in Figure 9. According to the projection, newsprint consumption is declining rather steadily up to 2010, after which the speed of decline increases. This pattern clearly reflects the assumptions made about the newspaper circulation decline. The newsprint circulation model forecast that in 2020 the newsprint consumption would be 7.6 million tons, which is equivalent to the level last experienced in the mid-1960s.

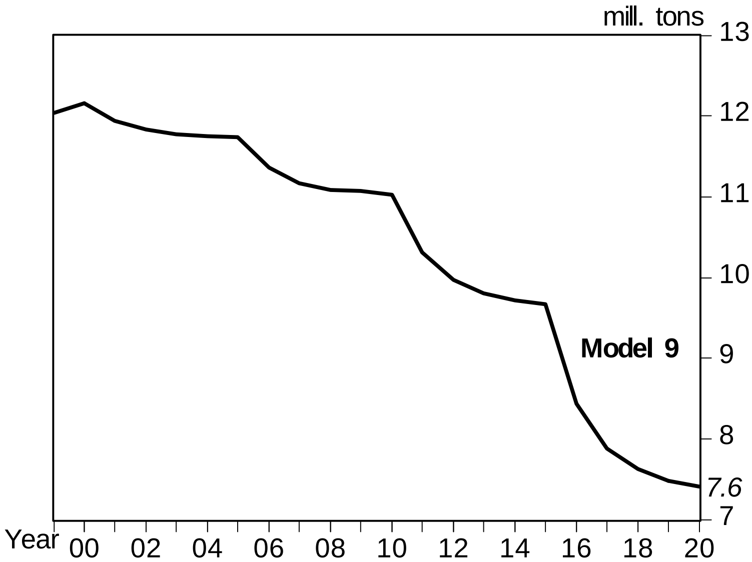

Figure 9: Forecasts from newspaper circulation model, 2001–2020.

5.5 Comparing the Forecasts

At least the following general conclusions can be drawn from comparing the various forecasts for US newsprint consumption (see Figure 10 and Tables 2 and 3). First, the older the data set used to estimate the forecasting model, the higher the long-term forecasts will be for US newsprint consumption. Thus, Model 3 (uses data for 1971–1987) and the FAO model (uses data for 1965–1994) clearly provide the highest projections. On the other hand, the more up-to-date the data set used to estimate the model, the worse will be the explanatory power and statistical robustness of the *classical model*. Indeed, the sign of the income (GDP) elasticity changes from positive to negative and becomes statistically insignificant when post-1987 data is used. Similarly, the newsprint price variable becomes insignificant.

The projections from the RPA model (Haynes, 2001), Model 4, and the Bayesian models (Models 7 and 8) provide very similar projections. These projections indicate a slight decline in newsprint consumption from today's level when moving towards 2020. Also, the newspaper circulation model (Model 9) provides rather similar forecasts with these models up to 2010. However, for the period 2010 to 2020, Model 9 provides much more rapidly declining consumption. If the substitution of electronic media (particularly the Internet) for newspaper reading accelerates from the rate observed in the last five years or so, the projections of Model 9 may very well turn out to be the most accurate of the various projections presented in this study.

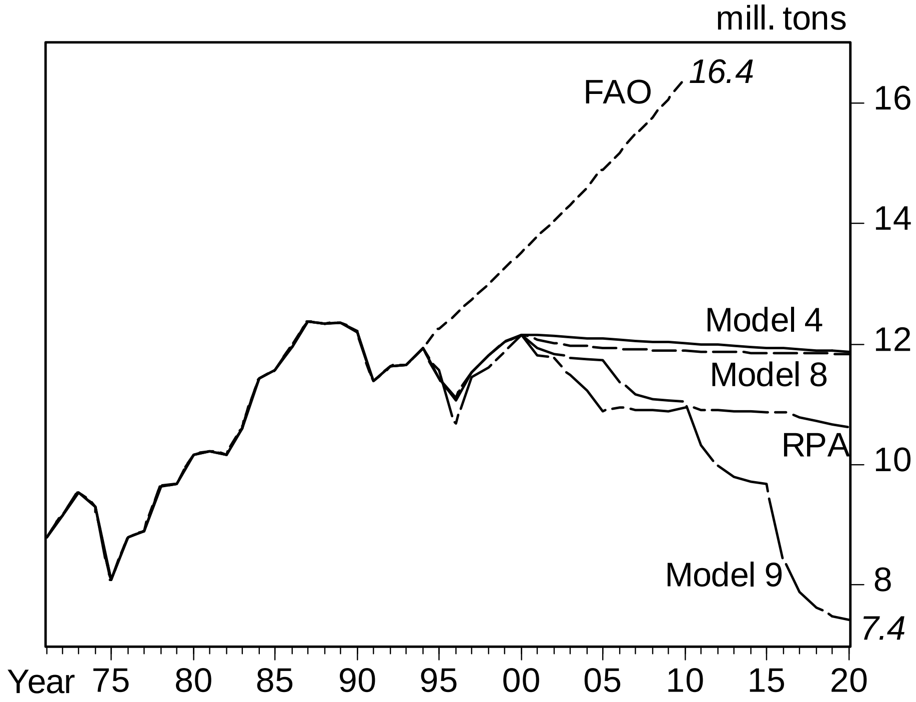

Figure 10: Forecasts from various models.

From the practical policy perspective, the differences in the projections are significant and troubling. Depending on whether newsprint consumption will follow the FAO projection or instead that of Model 9 or even the RPA projection, very different adjustments would be required in the US newsprint production and its imports (mainly from Canada). The FAO projection would imply more or less the “business-as-usual” pattern for the newsprint industry, while the Model 9 projection would imply major cuts in domestic productions and imports.

6 Summary and Conclusions

In the present study, forecasts for the US newsprint demand for 2001 to 2020 were computed using various approaches. The results shed light both on the methodological questions relating to modeling newsprint demand, as well as providing new forecasts for newsprint consumption.

The results indicated that the classical forest products demand model, still commonly used in forest economics literature, could not explain or forecast the recent structural change in the US newsprint consumption. Both the income (GDP) and newsprint price variable turned out to be insignificant determinants of newsprint demand. Moreover, the results of this study indicate that one should not rule out the possibility of negative income elasticity. However, the negative sign of the income elasticity is usually interpreted in the literature to be inconsistent with the demand theory and reflect an error in the model, estimation, or data (Simangunsong and Buongiorno, 2001; Buongiorno *et al*., 2001). So far, this may not have been a particularly large issue, since in the literature negative income elasticities for forest products demand are rarely reported. For example, Simangunsong and Buongiorno (2001) summarize the results from 9 studies published between 1978 and 2000, and the results show that for the 10 different forest product categories covered (including newsprint), not a single negative income elasticity was obtained.

Recent data and studies on the US media behavior point out that people read less newspapers, while simultaneously increasing the consumption of electronic media, especially the Internet (NAA, 2001; UCLA, 2001). It may be that economic wealth (i.e., GDP) is one of the factors that allow this substitution to take place. The higher the GDP, the more wealth households have to buy relative expensive computers and the services required, such as Internet accounts and modems. Also, the more households there are with access to the Internet, the more likely that there is substitution between printed newspapers and consumption of the Internet. Thus, this could imply negative income elasticity of demand for newsprint. On the other hand, it may be the case that at some income level newsprint consumption starts to be independent of income. Our estimation results suggest that the latter conclusion may be relevant for the US today.

In order to resolve the problems relating to the classical newsprint demand model, we proposed two alternative approaches — the Bayesian model and the newspaper circulation model. The Bayesian model allowed combining historical data with "forward looking" information concerning the GDP elasticity. This model should, however, be regarded more as an illustrative case of the Bayesian approach in a familiar classical setting, rather than a genuine alternative to the classical model. This means it presented a methodology that allows forest sector analysts to incorporate the 'future' into the conventional classical demand model by using informed prior. In future studies, the Bayesian approach could be extended in a number of ways that would differentiate it more clearly from the classical framework.

The newspaper circulation model is clearly an alternative to the classical model, since neither the GDP nor the newsprint price variable are included in forecasting long-term newsprint consumption. On the basis of pragmatic reasoning and data analysis, it was concluded that the changes in newspaper circulations could be an important indicator of future newsprint consumption. Consequently, an *ad hoc* newspaper circulation model was formulated and estimated. This very simple model performed rather well. However, a challenge remains in the future to extend the model to also include variables that could account for the changes in the size and grammage of newspapers. The latter factors will also directly affect the demand for newsprint. For example, the size of the average printed version of a newspaper and the grammage of newsprint is likely to decrease during 2001 to 2020. The major driving force behind this is the movement of advertisements (specially classified) to other media, and changes in editorial and other content to online-newspapers. Thus, these factors will most likely enhance the declining trend of newsprint demand.

The general conclusion from the study is that US newsprint consumption is more likely to decline than increase in the long-term. Of the various model specifications, the newsprint circulation model provided the lowest forecasts — 7.6 million tons for 2020 — which is equivalent of the level last experienced in the mid-1960s.

REFERENCES

Adams, D. and R. Haynes (1980). The 1980 Softwood Timber Assessment Market Model: Structure, Projections, and Policy Simulation. *Forest Science Monograph*, 22.

Allen, G. and R. Fields (1999). Econometric Forecasting Principles and Doubts: Unit Root Testing First, Last, or Never? Presented at the 19th International Symposium on Forecasting, 27–30 June 1999, Washington, DC, USA.

Baudin, A. and D. Brooks (1995). Projections of Forest Products Demand, Supply and Trade in ETTS V. ECE/TIM/DP/6. United Nations Economic Commission for Europe, Geneva, Switzerland.

Bauwens, L., M. Lubrano and J.-F. Richard (1999). *Bayesian Inference in Dynamic Econometric Models*. Oxford University Press, UK.

Buongiorno, J. (1977). Long-Term Forecasting of Major Forest Products Consumption in Developed and Developing Economies. *Forest Science*, Vol. 23, No. 1, pp. 13–25.

Buongiorno, J. (1996). Forest Sector Modeling: A Synthesis of Econometrics, Mathematical Programming, and System Dynamics Methods. *International Journal of Forecasting*, Vol. 12, pp. 329–343.

Buongiorno, J., C.-S. Liu and J. Turner (2001). Estimating International Wood and Fiber Utilization Accounts in the Presence of Measurement Errors. *Journal of Forest Economic*s, 7:2, pp. 101–128.

FAO (1999a). Global Forest Products Consumption, Production, Trade and Prices: Global Forest Products Model Projections to 2010. Working Paper GFPOS/WP/01, Food and Agriculture Organization of the United Nations (FAO), Rome, Italy.

FAO (1999b). The Global Forest Products Model (GFPM): Users Manual and Guide to Installation. Working Paper GFPOS/WP/02, Food and Agriculture Organization of the United Nations (FAO), Rome, Italy.

Fernandez, C., E. Ley and M. Steel (2001). Model Uncertainty in Cross-country Growth Regressions. *Journal of Applied Econometrics*, Vol. 16, Issue 5, pp. 563–576.

Hamilton, J.D. (1994). *Time Series Analysis*. Princeton University Press, Princeton, USA.

Haynes, R. (2001). An Analysis of the Timber Situation in the United States: 1997-2050. General Technical Report PNW-GTR-xxx. USDA Forest Service, Pacific Northwest Research Station, Portland, Oregon, USA, forthcoming.

Hendry, D.F. and J.A. Doornik (1997). *Empirical Econometric Modelling using PcGive 9.0 for Windows*. International Thomson Business Press, London, UK.

Kallio, M., D.P. Dykstra and C. Binkley, eds. (1987). *The Global Forest Sector: An Analytical Perspective*. Wiley, New York, USA.

Lutz, W. and A. Goujon (2001). The World's Changing Human Capital Stock: Multi-State Population Projection by Educational Attainment. *Population and Development Review*, 27(2), pp. 323–339, June.

McKillop, W.L.M. (1967). Supply and Demand for Forest Products — An Econometric Study. *Hilgardia*, 38 (1), pp. 1–132.

NAA (2001). Leveraging Newspaper Assets: A Study of Changing American Media Usage Habits, 2000. Research Report. Downloaded from and available on the Internet: http://www.naa.org. October 2001.

Obersteiner, M. (1998). The Pan Siberian Forest Industry Model (PSFIM): A Theoretical Concept for Forest Industry Analysis. Interim Report IR-98-033. International Institute for Applied Systems Analysis, Laxenburg, Austria.

Obersteiner, M. and S. Nilsson (2000). Press-imistic Futures? — Science Based Concepts and Models to Assess the Long-term Competitiveness of Paper Products in the Information Age. Interim Report IR-00-059. International Institute for Applied Systems Analysis, Laxenburg, Austria.

Pole, A., M. West and J. Harrison (1999). *Applied Bayesian Forecasting and Time Series Analysis*. Chapman and Hall, USA.

Pringle, S. (1954). An Econometric Analysis of the Demand for Newsprint in the United States. Ph.D. Dissertation, Syracuse University, USA.

Procter, A. (2000). Managing Technology for Value Delivery. Course Manuscript, Department of Wood Science, University of British Columbia, Vancouver, Canada.

Simangunsong, B.C.H. and J. Buongiorno (2001). International Demand Equations for Forest Products: A Comparison of Methods. *Scandinavian Journal of Forest Research*, 16, pp. 155–172.

Solberg, B. and A. Moiseyev, eds. (1997). Demand and Supply Analyses of Roundwood and Forest Products Markets in Europe — Overview of Present Studies. First Workshop of the Concerted Action Project AIR3-CT942288, Helsinki, Finland, 3–5 November 1995, Helsinki, 1997. EFI Proceedings No. 17, European Forest Institute (EFI), Helsinki, Finland, 418 p.

Statistical Abstracts of the United States (2000). US Census Bureau. Downloaded from and available on the Internet: http://www.census.gov/statab/www/.

UCLA (2001). Surveying the Digital Future: Year Two. University of California, Los Angeles (UCLA) Internet Report 2001, Center for Communication Policy. Downloaded from and available on the Internet: http://ccp.ucla.edu, 29 November 2001.

West, M. and J. Harrison (1997). *Bayesian Forecasting and Dynamic Models*. Springer-Verlag Series in Statistics, USA.

Zhang, Y. and J. Buongiorno (1997). Communication Media and Demand for Printing and Publishing Papers in the United States. *Forest Science*, Vol. 43, No. 3, pp. 362–377.

Zhang, Y., J. Buongiorno and P. Ince (1993). PELPS III: A Microcomputer Price-endogenous Linear Programming System for Economic Modeling. Research Paper FPL-RP-526. USDA Forest Service, Forest Product Laboratory, Madison, Wisconsin, USA.

Appendix I: The Bayesian Normal-Gamma Regression Model

Consider the linear regression model:

$$Y_t = x_t'\beta + u_t$$

where $u_t \approx i.i.d.N(0,\sigma^2)$, x_t is a (*kx1*) vector of exogenous explanatory variables, and β is a (*k x 1*) vector of coefficients. Let

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_T \end{bmatrix} \qquad X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_T \end{bmatrix}$$

where y is a (*T x 1*) vector and X is a (T x k) matrix. σ^2 and β are both regarded as random variables. The prior distribution for σ^2 is given by the gamma distribution. Instead of describing the prior distribution in terms of the variance σ^2 it is convenient to take the reciprocal of the variance, σ^{-2}, which is known as the precision:

$$f(\sigma^{-2}|X) = \frac{(\lambda^*/2)^{N^*/2}\sigma^{-2[(N^*/2)-1]}\exp[-\lambda^*\sigma^{-2}/2]}{\Gamma(N^*/2)} \tag{A1}$$

where N^* and λ^* are parameters that describe the analyst's prior information. The prior distribution of β conditional on the value for σ^2 is given by:

$$f(\beta|\sigma^{-2},X) = \frac{1}{(2\pi\sigma^2)^{k/2}}|H^*|^{-1/2}\exp\left\{\left(-\frac{1}{(2\sigma^2)}\right)(\beta-b^*)'H^{*-1}(\beta-b^*)\right\} \tag{A2}$$

Thus, prior to observation of the sample, the analyst's best guess for the value of β is represented by the (*k x 1*) vector b* and the confidence in this guess is summarized by the (k x k) matrix H*; less confidence is represented by larger diagonal elements of H*.

Thus, $f(\beta,\sigma^{-2}|X)$, the joint prior density for β and σ^2, is given by the product of equations (A1) and (A2). The posterior distribution $f(\beta,\sigma^{-2}|y,X)$ is described by the following proposition (see Hamilton, 1994:356–357).

Proposition:[14] *Let the prior density* $f(\beta,\sigma^{-2}|X)$ *be given by the product of equations (A1) and (A2), and let the sample likelihood be:*

[14] For proof see Hamilton (1994:367–369).

$$f(y|\beta,\sigma^{-2},X)=\frac{1}{\left(2\pi\sigma^{2}\right)^{T/2}}\exp\left\{\left[\frac{1}{2\sigma^{2}}\right](y-X\beta)'(y-X\beta)\right\}. \tag{A3}$$

Then the following hold: The joint posterior density of β and σ^{-2} is given by:

$$f(\beta,\sigma^{-2}|b,X)=f(\beta|\sigma^{-2},y,X)\cdot f(\sigma^{-2}|y,X) \tag{A4}$$

where the posterior distribution of β is conditional on σ^{-2} is $N\left(b^{**},bH^{**}\right)$:

$$f(\beta|\sigma^{-2},y,X)=\frac{1}{(2\pi\sigma^{2})^{k/2}}\left|H^{*}\right|^{-1/2}\exp\left\{\left(-\frac{1}{(2\sigma^{2})}\right)\left(\beta-b^{**}\right)'H^{**-1}\left(\beta-b^{**}\right)\right\} \tag{A5}$$

with

$$b^{**}=\left(H^{*-1}+X'X\right)^{-1}\left(H^{*-1}b^{*}+X'y\right) \tag{A8}$$

$$H^{**}=\left(H^{*-1}+X'X\right)^{-1}. \tag{A7}$$

Furthermore, the marginal posterior distribution of σ^{-2} is $\Gamma\left(N^{**},\lambda^{**}\right)$:

$$f(\sigma^{-2}|y,X)=\frac{\left(\lambda^{**}/2\right)^{N^{**}/2}\sigma^{-2\left[\left(N^{**}/2\right)-1\right]}}{\Gamma\left(N^{**}/2\right)}\exp\left[-\lambda^{**}\sigma^{-2}/2\right], \tag{A8}$$

with

$$N^{**}=N^{*}+T$$

$$\lambda^{**}=\lambda^{*}+(y-Xb)'(y-Xb)+\left(b-b^{*}\right)'H^{*-1}\left(X'X+H^{*-1}\right)^{-1}\left(b-b^{*}\right) \tag{A9}$$

for $b=(X'X)^{-1}X'y$ the OLS estimator.

The Bayesian estimate of the precision is then given by:

$$E\left(\sigma^{-2}|y,X\right)=N^{**}/\lambda^{**}$$

For a more detailed description of the Normal-Gamma regression model see, e.g., Hamilton (1994) and Obersteiner (1998).

Appendix II: Time Series Properties of the Data

Descriptive Statistics 1971–2000 (30 observations).

	LNEWS	LGDP	LPRICE
Mean	2.371493	8.662462	1.878485
Median	2.433656	8.668003	1.918916
Maximum	2.515678	9.139757	2.069261
Minimum	2.090307	8.215466	1.569125
Std. Dev.	0.125774	0.266045	0.163494
Skewness	-0.611043	0.059246	-0.692173
Kurtosis	2.071733	1.876962	2.222391
Jarque-Bera	2.943965	1.594070	3.151364
Probability	0.229470	0.450663	0.206866
Sum	71.14480	259.8739	56.35454
Sum Sq. Dev.	0.458757	2.052620	0.775182

Descriptive Statistics 1987–2000 (14 observations).

	LNEWS	LGDP	LPRICE	LCIRC
Mean	2.471737	8.904916	1.766505	-0.008136
Median	2.473999	8.882356	1.762628	-0.005502
Maximum	2.515678	9.139757	2.036388	0.005170
Minimum	2.407035	8.718222	1.569125	-0.026681
Std. Dev.	0.034614	0.129704	0.162834	0.008616
Skewness	-0.262347	0.385616	0.172895	-0.814036
Kurtosis	1.907954	1.996258	1.641699	2.948075
Jarque-Bera	0.856256	0.934673	1.145990	1.547765
Probability	0.651728	0.626669	0.563834	0.461219
Sum	34.60432	124.6688	24.73108	-0.113909
Sum Sq. Dev.	0.015576	0.218702	0.344694	0.000965

Correlation matrix 1971–2000.

	LNEWS	LGDP	LPRICE
LNEWS	1.000000	0.853145	-0.482061
LGDP	0.853145	1.000000	-0.645744
LPRICER	-0.482061	-0.645744	1.000000

Correlation matrix 1971–1987.

	LNEWS	LGDP	LPRICE
LNEWS	1.000000	0.914902	-0.086354
LGDP	0.914902	1.000000	0.273656
LPRICER	-0.086354	0.273656	1.000000

Correlation matrix 1987–2000.

	LNEWS	LGDP	LPRICE	LCIRC
LNEWS	1.000000	-0.245365	0.295374	0.836755
LGDP	-0.245365	1.000000	-0.555644	-0.115412
LPRICER	0.295374	-0.555644	1.000000	0.071325
LCIRCCH	0.836755	-0.115412	0.071325	1.000000

Correlograms for LNEWS and First Difference of LNEWS: Samples 1971–2000 and 1987–2000.

LNEWS/Sample: 1971–2000/Observations: 30

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. |*******|	. |*******|	1	0.875	0.875	25.319	0.000
. |****** |	. | . |	2	0.767	0.011	45.511	0.000
. |***** |	. | . |	3	0.681	0.032	61.994	0.000
. |***** |	. | . |	4	0.610	0.024	75.713	0.000
. |**** |	.**| . |	5	0.471	-0.318	84.214	0.000
. |*** |	. | . |	6	0.351	-0.031	89.146	0.000
. |**. |	.**| . |	7	0.211	-0.220	91.005	0.000
. |* . |	. | . |	8	0.103	-0.002	91.472	0.000
. | . |	. | . |	9	-0.006	-0.036	91.474	0.000
. *| . |	. |* . |	10	-0.069	0.094	91.706	0.000

First Difference LNEWS/Sample: 1971–2000/Observations: 29

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. | . |	. | . |	1	-0.041	-0.041	0.0537	0.817
. | . |	. | . |	2	-0.029	-0.031	0.0815	0.960
.**| . |	.**| . |	3	-0.210	-0.213	1.6092	0.657
. |* . |	. | . |	4	0.077	0.060	1.8237	0.768
. | . |	. | . |	5	0.000	-0.009	1.8237	0.873
. | . |	. | . |	6	0.042	0.002	1.8935	0.929
. | . |	. | . |	7	0.021	0.054	1.9112	0.965
. | . |	. | . |	8	-0.022	-0.026	1.9318	0.983
.**| . |	.**| . |	9	-0.198	-0.197	3.6904	0.931
. | . |	. | . |	10	-0.039	-0.047	3.7636	0.957

LNEWS/Sample: 1987–2000/Observations: 14

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. |**** |	. |**** |	1	0.557	0.557	5.3401	0.021
. |* . |	. **| . |	2	0.136	-0.252	5.6841	0.058
. *| . |	. *| . |	3	-0.126	-0.124	6.0079	0.111
. *| . |	. | . |	4	-0.141	0.054	6.4539	0.168
. | . |	. |* . |	5	0.004	0.111	6.4543	0.264
. *| . |	.***| . |	6	-0.178	-0.444	7.3456	0.290
.***| . |	. *| . |	7	-0.334	-0.105	10.907	0.143
.***| . |	. *| . |	8	-0.419	-0.142	17.470	0.026
. **| . |	. | . |	9	-0.297	-0.041	21.416	0.011
. | . |	. |* . |	10	0.009	0.078	21.421	0.018

First Difference LNEWS/Sample: 1987–2000/Observations: 14

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. | . |	. | . |	1	-0.002	-0.002	9.E-05	0.992
. *| . |	. *| . |	2	-0.155	-0.155	0.4474	0.800
. **| . |	. **| . |	3	-0.246	-0.253	1.6770	0.642
. *| . |	. *| . |	4	-0.065	-0.109	1.7703	0.778
. |***. |	. |** . |	5	0.334	0.273	4.5407	0.474
. *| . |	. **| . |	6	-0.129	-0.225	5.0087	0.543
. | . |	. | . |	7	-0.053	-0.016	5.0970	0.648
. **| . |	. *| . |	8	-0.226	-0.166	7.0094	0.536
. *| . |	. **| . |	9	-0.167	-0.262	8.2529	0.509
. |* . |	. *| . |	10	0.084	-0.141	8.6455	0.566

Correlograms for LGDP and First Difference of LGDP: Samples 1971–2000 and 1987–2000.

LGDP/Sample: 1971–2000/Observations: 30

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. |*******|	. |*******|	1	0.886	0.886	25.959	0.000
. |****** |	. | . |	2	0.779	-0.022	46.789	0.000
. |***** |	. | . |	3	0.684	-0.007	63.445	0.000
. |**** |	. *| . |	4	0.588	-0.062	76.190	0.000
. |**** |	. *| . |	5	0.489	-0.065	85.384	0.000
. |*** |	. | . |	6	0.399	-0.028	91.767	0.000
. |**. |	. | . |	7	0.315	-0.038	95.907	0.000
. |**. |	. | . |	8	0.242	-0.007	98.462	0.000
. |* . |	. | . |	9	0.172	-0.041	99.817	0.000
. |* . |	. *| . |	10	0.100	-0.066	100.30	0.000

First Difference LGDP/Sample: 1971–2000/Observations: 29

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. |* . |	. |* . |	1	0.189	0.189	1.1455	0.284
.**| . |	.**| . |	2	-0.238	-0.284	3.0351	0.219
.**| . |	. *| . |	3	-0.252	-0.159	5.2350	0.155
.**| . |	.**| . |	4	-0.241	-0.254	7.3266	0.120
. |* . |	. |* . |	5	0.074	0.070	7.5331	0.184
. | . |	.**| . |	6	0.013	-0.213	7.5396	0.274
. | . |	. *| . |	7	-0.027	-0.060	7.5702	0.372
. |* . |	. | . |	8	0.088	0.015	7.9048	0.443
. *| . |	.**| . |	9	-0.147	-0.250	8.8701	0.449
. *| . |	. *| . |	10	-0.099	-0.101	9.3318	0.501

LGDP/Sample: 1987–2000/Observations: 14

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. |****** |	. |****** |	1	0.758	0.758	9.8876	0.002
. |**** |	. *| . |	2	0.544	-0.070	15.411	0.000
. |***. |	. *| . |	3	0.355	-0.077	17.980	0.000
. |* . |	. *| . |	4	0.185	-0.091	18.747	0.001
. | . |	. *| . |	5	0.015	-0.141	18.752	0.002
. *| . |	. *| . |	6	-0.130	-0.103	19.222	0.004
. **| . |	. *| . |	7	-0.256	-0.127	21.319	0.003
.***| . |	. | . |	8	-0.331	-0.054	25.404	0.001
.***| . |	. *| . |	9	-0.378	-0.082	31.789	0.000
.***| . |	. | . |	10	-0.379	-0.033	39.840	0.000

First Difference LGDP/Sample: 1987–2000/Observations: 14

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. |***. |	. |***. |	1	0.390	0.390	2.6152	0.106
. |* . |	. | . |	2	0.140	-0.014	2.9827	0.225
. *| . |	. **| . |	3	-0.120	-0.201	3.2759	0.351
. | . |	. |* . |	4	0.017	0.163	3.2820	0.512
. *| . |	. *| . |	5	-0.072	-0.125	3.4108	0.637
. *| . |	. *| . |	6	-0.154	-0.174	4.0785	0.666
. **| . |	. *| . |	7	-0.296	-0.160	6.8871	0.441
. **| . |	. | . |	8	-0.204	-0.039	8.4438	0.391
. **| . |	. **| . |	9	-0.260	-0.233	11.481	0.244
. | . |	. |* . |	10	-0.054	0.081	11.647	0.309

Correlograms for LPRICE and First Difference of LPRICE: Samples 1971–2000 and 1987–2000.

LPRICE/Sample: 1971–2000/Observations: 30

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>. |****** |</td><td>. |****** |</td><td>1</td><td>0.782</td><td>0.782</td><td>20.248</td><td>0.000</td></tr>
<tr><td>. |**** |</td><td>. *| . |</td><td>2</td><td>0.554</td><td>-0.148</td><td>30.773</td><td>0.000</td></tr>
<tr><td>. |*** |</td><td>. | . |</td><td>3</td><td>0.404</td><td>0.058</td><td>36.567</td><td>0.000</td></tr>
<tr><td>. |**. |</td><td>. | . |</td><td>4</td><td>0.279</td><td>-0.056</td><td>39.445</td><td>0.000</td></tr>
<tr><td>. |**. |</td><td>. |*** |</td><td>5</td><td>0.317</td><td>0.349</td><td>43.302</td><td>0.000</td></tr>
<tr><td>. |*** |</td><td>. *| . |</td><td>6</td><td>0.345</td><td>-0.060</td><td>48.064</td><td>0.000</td></tr>
<tr><td>. |**. |</td><td>. *| . |</td><td>7</td><td>0.294</td><td>-0.069</td><td>51.664</td><td>0.000</td></tr>
<tr><td>. |* . |</td><td>***| . |</td><td>8</td><td>0.139</td><td>- 0.330</td><td>52.502</td><td>0.000</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>9</td><td>-0.046</td><td>-0.056</td><td>52.600</td><td>0.000</td></tr>
<tr><td>. *| . |</td><td>. | . |</td><td>10</td><td>-0.144</td><td>-0.004</td><td>53.592</td><td>0.000</td></tr>
</table>

First Difference LPRICE/Sample: 1971–2000/Observations: 29

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>. | . |</td><td>. | . |</td><td>1</td><td>-0.026</td><td>-0.026</td><td>0.0213</td><td>0.884</td></tr>
<tr><td>. *| . |</td><td>. *| . |</td><td>2</td><td>-0.094</td><td>-0.095</td><td>0.3164</td><td>0.854</td></tr>
<tr><td>. *| . |</td><td>. *| . |</td><td>3</td><td>-0.113</td><td>-0.119</td><td>0.7559</td><td>0.860</td></tr>
<tr><td>.**| . |</td><td>***| . |</td><td>4</td><td>-0.301</td><td>-0.326</td><td>4.0214</td><td>0.403</td></tr>
<tr><td>. |* . |</td><td>. | . |</td><td>5</td><td>0.067</td><td>0.010</td><td>4.1914</td><td>0.522</td></tr>
<tr><td>. | . |</td><td>. *| . |</td><td>6</td><td>-0.054</td><td>-0.152</td><td>4.3046</td><td>0.636</td></tr>
<tr><td>. |**. |</td><td>. |**. |</td><td>7</td><td>0.264</td><td>0.215</td><td>7.1506</td><td>0.413</td></tr>
<tr><td>. |* . |</td><td>. | . |</td><td>8</td><td>0.067</td><td>-0.030</td><td>7.3421</td><td>0.500</td></tr>
<tr><td>. *| . |</td><td>. | . |</td><td>9</td><td>-0.070</td><td>0.014</td><td>7.5624</td><td>0.579</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>10</td><td>0.008</td><td>-0.004</td><td>7.5652</td><td>0.671</td></tr>
</table>

LPRICE/Sample: 1987–2000/Observations: 14

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>. |**** |</td><td>. |**** |</td><td>1</td><td>0.569</td><td>0.569</td><td>5.5799</td><td>0.018</td></tr>
<tr><td>. |* . |</td><td>. **| . |</td><td>2</td><td>0.121</td><td>-0.300</td><td>5.8544</td><td>0.054</td></tr>
<tr><td>. *| . |</td><td>. *| . |</td><td>3</td><td>-0.178</td><td>-0.157</td><td>6.4961</td><td>0.090</td></tr>
<tr><td>.***| . |</td><td>. **| . |</td><td>4</td><td>-0.358</td><td>-0.205</td><td>9.3600</td><td>0.053</td></tr>
<tr><td>. **| . |</td><td>. |* . |</td><td>5</td><td>-0.205</td><td>0.192</td><td>10.407</td><td>0.064</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>6</td><td>-0.004</td><td>-0.005</td><td>10.407</td><td>0.109</td></tr>
<tr><td>. |* . |</td><td>. |* . |</td><td>7</td><td>0.171</td><td>0.105</td><td>11.340</td><td>0.124</td></tr>
<tr><td>. |* . |</td><td>. *| . |</td><td>8</td><td>0.156</td><td>-0.152</td><td>12.249</td><td>0.140</td></tr>
<tr><td>. *| . |</td><td>. **| . |</td><td>9</td><td>-0.090</td><td>-0.217</td><td>12.615</td><td>0.181</td></tr>
<tr><td>. **| . |</td><td>. |* . |</td><td>10</td><td>-0.194</td><td>0.066</td><td>14.719</td><td>0.143</td></tr>
</table>

First Difference LPRICE/Sample: 1987–2000/Observations: 14

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>. *| . |</td><td>. *| . |</td><td>1</td><td>-0.069</td><td>-0.069</td><td>0.0821</td><td>0.774</td></tr>
<tr><td>. *| . |</td><td>. *| . |</td><td>2</td><td>-0.104</td><td>-0.110</td><td>0.2851</td><td>0.867</td></tr>
<tr><td>. **| . |</td><td>. **| . |</td><td>3</td><td>-0.189</td><td>-0.208</td><td>1.0108</td><td>0.799</td></tr>
<tr><td>.***| . |</td><td>.***| . |</td><td>4</td><td>-0.360</td><td>-0.432</td><td>3.9200</td><td>0.417</td></tr>
<tr><td>. |* . |</td><td>. *| . |</td><td>5</td><td>0.091</td><td>-0.088</td><td>4.1260</td><td>0.531</td></tr>
<tr><td>. *| . |</td><td>.***| . |</td><td>6</td><td>-0.134</td><td>-0.380</td><td>4.6250</td><td>0.593</td></tr>
<tr><td>. |** . |</td><td>. | . |</td><td>7</td><td>0.256</td><td>-0.032</td><td>6.7246</td><td>0.458</td></tr>
<tr><td>. |* . |</td><td>. *| . |</td><td>8</td><td>0.129</td><td>-0.135</td><td>7.3482</td><td>0.500</td></tr>
<tr><td>. *| . |</td><td>. **| . |</td><td>9</td><td>-0.086</td><td>-0.195</td><td>7.6789</td><td>0.567</td></tr>
<tr><td>. | . |</td><td>. **| . |</td><td>10</td><td>0.001</td><td>-0.238</td><td>7.6789</td><td>0.660</td></tr>
</table>

Correlogram for ΔLCIRC.

ΔLCIRC/Sample: 1987–2000/Observations: 14

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>. |** . |</td><td>. |** . |</td><td>1</td><td>0.210</td><td>0.210</td><td>0.7625</td><td>0.383</td></tr>
<tr><td>. *| . |</td><td>. *| . |</td><td>2</td><td>-0.097</td><td>-0.148</td><td>0.9383</td><td>0.626</td></tr>
<tr><td>. *| . |</td><td>. *| . |</td><td>3</td><td>-0.117</td><td>-0.067</td><td>1.2158</td><td>0.749</td></tr>
<tr><td>. *| . |</td><td>. *| . |</td><td>4</td><td>-0.129</td><td>-0.108</td><td>1.5892</td><td>0.811</td></tr>
<tr><td>. |* . |</td><td>. |** . |</td><td>5</td><td>0.161</td><td>0.208</td><td>2.2340</td><td>0.816</td></tr>
<tr><td>. *| . |</td><td>. **| . |</td><td>6</td><td>-0.154</td><td>-0.309</td><td>2.9010</td><td>0.821</td></tr>
<tr><td>. *| . |</td><td>. | . |</td><td>7</td><td>-0.123</td><td>0.029</td><td>3.3829</td><td>0.847</td></tr>
<tr><td>. **| . |</td><td>.***| . |</td><td>8</td><td>-0.295</td><td>-0.394</td><td>6.6420</td><td>0.576</td></tr>
<tr><td>. **| . |</td><td>. | . |</td><td>9</td><td>-0.238</td><td>-0.044</td><td>9.1773</td><td>0.421</td></tr>
<tr><td>. |* . |</td><td>. *| . |</td><td>10</td><td>0.089</td><td>-0.095</td><td>9.6229</td><td>0.474</td></tr>
</table>

First Difference ΔLCIRC/Sample: 1987–2000/Observations: 13

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>. **| . |</td><td>. **| . |</td><td>1</td><td>-0.281</td><td>-0.281</td><td>1.2786</td><td>0.258</td></tr>
<tr><td>. **| . |</td><td>. **| . |</td><td>2</td><td>-0.209</td><td>-0.312</td><td>2.0511</td><td>0.359</td></tr>
<tr><td>. | . |</td><td>. *| . |</td><td>3</td><td>0.021</td><td>-0.173</td><td>2.0596</td><td>0.560</td></tr>
<tr><td>. | . |</td><td>. *| . |</td><td>4</td><td>0.053</td><td>-0.080</td><td>2.1210</td><td>0.714</td></tr>
<tr><td>. |** . |</td><td>. |** . |</td><td>5</td><td>0.247</td><td>0.265</td><td>3.6029</td><td>0.608</td></tr>
<tr><td>.***| . |</td><td>. *| . |</td><td>6</td><td>-0.320</td><td>-0.155</td><td>6.4559</td><td>0.374</td></tr>
<tr><td>. |* . |</td><td>. |* . |</td><td>7</td><td>0.166</td><td>0.188</td><td>7.3505</td><td>0.393</td></tr>
<tr><td>. | . |</td><td>. *| . |</td><td>8</td><td>-0.051</td><td>-0.086</td><td>7.4537</td><td>0.489</td></tr>
<tr><td>. *| . |</td><td>. *| . |</td><td>9</td><td>-0.121</td><td>-0.150</td><td>8.1705</td><td>0.517</td></tr>
<tr><td>. | . |</td><td>. *| . |</td><td>10</td><td>0.031</td><td>-0.187</td><td>8.2333</td><td>0.606</td></tr>
</table>

ADF Unit Root Tests.

Variable	ADF-test statistic Constant, C	ADF-test statistic C and trend	Decision Constant, C	Decision C and trend
LNEWS (sample 1971–2000)	ADF(3): -1.07	ADF(3): -1.20	I(1)	I(1)
LGDP (sample 1971–2000)	ADF(1): -0.29	ADF(1): -3.09	I(1)	I(1)
LGDPPC (sample 1971–2000)	ADF(1): -0.25	ADF(1): -2.74	I(1)	I(1)
LPRICE (sample 1971–2000)	ADF(1): -1.28	ADF(1): -3.29	I(1)	I(1)
LCIRC (sample 1987–2000)	ADF(1): -3.04		I(0) or I(1)	

Note: (i) Critical values for the ADF test are 5% = -2.98 and 1% = -3.71 with constant; 5% = -3.59 and 1% = -4.35 with constant and trend included for the sample 1971–2000; (ii) for the sample 1987–2000, critical values for the ADF test are 5% = -3.18 and 1% = -4.22 with constant; (iii) in the cases where the ADF test indicated the series not to be I(0), the ADF test was run for the first difference of the variables to analyze whether the series could be regarded to be either I(1) or I(2). These ADF results are not reported here, but they are taken into account in determining the order of integration in the "Decision" column of the Table; (iv) also, the Table presents only test values of the highest lag with a significant t-value (a method suggested by Hendry and Doornik, 1997). The lag order is shown in parentheses.

Philips-Perron Unit Root Tests.

Variable	ADF-test statistic Constant, C	ADF-test statistic C and trend	Decision Constant, C	Decision C and trend
LNEWS (sample 1971–2000)	-1.34	-1.76	I(1)	I(1)
LGDP (sample 1971–2000)	-0.29	-2.58	I(1)	I(1)
LGDPPC (sample 1971–2000)	-0.27	-2.40	I(1)	I(1)
LPRICE (sample 1971–2000)	-1.43	-2.67	I(1)	I(1)
LCIRC (sample 1987–2000)	-2.98		I(0) or I(1)	

The tests were run using the same lag order for the series as in the ADF test. Critical values for the PP test with constant and for the sample 1971–2000 are 10% = -2.62, 5% = -2.97 and 1% = -3.67; and with constant and trend included 10% = 3.33, 5% = -3.57 and 1% = -4.31. For the sample 1987–2000, critical values for the PP test with constant are 10% = 2.70, 5% = -3.12 and 1% = -4.07.

COINTEGRATION TESTS: SUMMARY

Included observations: 28

Series: LNEWS; LGDP; LPRICER

Lags interval: 1 to 1

Data Trend:	**None**	**None**	**Linear**	**Linear**	**Quadratic**
Rank or No. of CEs	**No Intercept No Trend**	**Intercept No Trend**	**Intercept No Trend**	**Intercept Trend**	**Intercept Trend**
Selected (5% level) No. of Cointegrating Relations by Model (columns)					
Trace	**1**	**1**	**0**	**0**	**0**
Max-Eig	**1**	**0**	**0**	**0**	**0**
Log Likelihood by Rank (rows) and Model (columns)					
0	146.8943	146.8943	153.9282	153.9282	156.6563
1	156.9308	157.1370	160.5533	161.8094	164.5057
2	158.9451	162.4422	163.3464	167.5435	170.1429
3	160.2562	164.4300	164.4300	170.2447	170.2447
Akaike Information Criteria by Rank (rows) and Model (columns)					
0	-9.849594	-9.849594	-10.13773	-10.13773	-10.11831
1	-10.13791	-10.08121	-10.18238	-10.20067	**-10.25041***
2	-9.853223	-9.960156	-9.953317	-10.11025	-10.22449
3	-9.518301	-9.602145	-9.602145	-9.803191	-9.803191
Schwarz Criteria by Rank (rows) and Model (columns)					
0	-9.421386	-9.421386	**-9.566782***	**-9.566782***	-9.404628
1	-9.424232	-9.319953	-9.325965	-9.296675	-9.251254
2	-8.854070	-8.865845	-8.811428	-8.873202	-8.939864
3	-8.233675	-8.174783	-8.174783	-8.233093	-8.233093

Appendix III: Estimation Results

Explanations of the acronyms used for mis-specification tests (for more details, see Hendry and Doornik, 1997):

AR 1- 2	=	Breusch-Godfrey Error Autocorrelation Test (2nd Order)
ARCH 1	=	Autoregressive Conditional Heteroskedasticity Test (1st Order)
Normality Chi^2	=	Doornik-Hansen Normality Test
Xi^2	=	Heteroscedasticity Test (squares) tests for The residuals being heteroscedastic owing to omitting squares of the regressors.
Xi*Xj	=	White test for heteroscedasticity, which includes all squares (as in the previous heteroscedasticity test) and all cross-products of variables.
RESET	=	Ramsey Reset Test for Functional Form (1st Order)

ESTIMATION RESULTS: Model 1

Model 1 Modeling LNEWS by OLS

The present sample is: **1972 to 2000**

Variable	Coefficient	Std.Error	t-value	t-prob	PartR^2
Constant	-0.093817	0.55356	-0.169	0.8668	0.0011
LNEWS_1	0.76696	0.12595	6.089	0.0000	0.5973
LGDP	0.078285	0.074770	1.047	0.3051	0.0420
LPRICER	-0.012089	0.072017	-0.168	0.8680	0.0011

```
R^2 = 0.883421  Adj R^2 = 0.87
F(3,25) = 63.149 [0.0000]  \sigma = 0.0441693  DW = 1.81
RSS = 0.04877310936 for 4 variables and 29 observations
```

```
AR 1- 2 F( 2, 23) =     0.60113  [0.5566]
ARCH 1  F( 1, 23) =     0.015485 [0.9020]
Normality Chi^2(2)=    11.623    [0.0030] **
Xi^2    F( 6, 18) =     1.0597   [0.4216]
Xi*Xj   F( 9, 15) =     0.96088  [0.5060]
RESET   F( 1, 24) =     0.053359 [0.8193]
```

```
Solved Static Long Run equation
LNEWS =   -0.4026              +0.3359 LGDP        -0.05188 LPRICER
(SE)     (    2.285)          (   0.2079)          (   0.3169)

ECM = LNEWS + 0.402583 - 0.335931*LGDP + 0.0518778*LPRICER;

WALD test Chi^2(2) = 6.4823 [0.0391] *
```

ESTIMATION RESULTS: Model 2

Model 2 Estimating the unrestricted reduced form VAR by OLS

```
The present sample is:  1972 to 2000

URF Equation 1 for LNEWS
Variable      Coefficient    Std.Error    t-value    t-prob
LNEWS_1        0.78747       0.13068       6.026     0.0000
LGDP_1         0.088514      0.072595      1.219     0.2341
LPRICER_1      0.054199      0.067408      0.804     0.4289
Constant      -0.35328       0.50275      -0.703     0.4887

\sigma = 0.044611   RSS = 0.04975351739

URF Equation 2 for LGDP
Variable      Coefficient    Std.Error    t-value    t-prob
LNEWS_1       -0.081522      0.063901     -1.276     0.2138
LGDP_1         1.0350        0.035498     29.156     0.0000
LPRICER_1     -0.0098797     0.032962     -0.300     0.7669
Constant      -0.058922      0.24584      -0.240     0.8125

\sigma = 0.0218144   RSS = 0.01189665755

URF Equation 3 for LPRICER
Variable      Coefficient    Std.Error    t-value    t-prob
LNEWS_1        0.26099       0.26963       0.968     0.3423
LGDP_1        -0.31579       0.14978      -2.108     0.0452
LPRICER_1      0.62725       0.13908       4.510     0.0001
Constant       2.8090        1.0373        2.708     0.0120

\sigma = 0.0920452   RSS = 0.211807786

correlation of URF residuals
                   LNEWS        LGDP         LPRICER
 LNEWS             1.0000
 LGDP              0.65867      1.0000
 LPRICER          -0.28652     -0.14793      1.0000

standard deviations of URF residuals
        LNEWS        LGDP        LPRICER
        0.044611     0.021814    0.092045

loglik = 286.28658  log|\Omega| = -19.7439  |\Omega| = 2.66276e-009  T
= 29
log|Y'Y/T| = -12.5194
R^2(LR) = 0.999271  R^2(LM) = 0.701693
```

```
F-test on all regressors except unrestricted, F(9,56) = 115.13
[0.0000] **
variables entered unrestricted:
  Constant

F-tests on retained regressors, F(3, 23)
    LNEWS_1     29.2008 [0.0000] **     LGDP_1     440.737 [0.0000] **
  LPRICER_1     8.29339 [0.0006] **

correlation of actual and fitted
        LNEWS        LGDP        LPRICER
        0.93866      0.99677     0.85220

LNEWS   :Portmanteau  4 lags=   1.8175
LGDP    :Portmanteau  4 lags=   7.2246
LPRICER :Portmanteau  4 lags=   4.8688
LNEWS   :AR 1- 2 F( 2, 23) =    0.032583  [0.9680]
LGDP    :AR 1- 2 F( 2, 23) =    1.3011    [0.2915]
LPRICER :AR 1- 2 F( 2, 23) =    0.16683   [0.8474]
LNEWS   :Normality Chi^2(2)=   12.452     [0.0020] **
LGDP    :Normality Chi^2(2)=    2.9482    [0.2290]
LPRICER :Normality Chi^2(2)=   10.765     [0.0046] **
LNEWS   :ARCH 1  F( 1, 23) =    0.047645  [0.8291]
LGDP    :ARCH 1  F( 1, 23) =    0.099153  [0.7557]
LPRICER :ARCH 1  F( 1, 23) =    0.1498    [0.7023]
LNEWS   :Xi^2    F( 6, 18) =    0.39517   [0.8725]
LGDP    :Xi^2    F( 6, 18) =    1.2005    [0.3504]
LPRICER :Xi^2    F( 6, 18) =    1.0775    [0.4119]
LNEWS   :Xi*Xj   F( 9, 15) =    0.58891   [0.7870]
LGDP    :Xi*Xj   F( 9, 15) =    0.77431   [0.6423]
LPRICER :Xi*Xj   F( 9, 15) =    0.84837   [0.5862]
Vector portmanteau  4 lags=     29.7
Vector AR 1-2  F(18, 48) =      1.0994    [0.3814]
Vector normality Chi^2( 6)=    31.284     [0.0000] **
Vector  Xi^2   F(36, 59) =      0.97272   [0.5270]
Vector  Xi*Xj  F(54, 55) =      0.77746   [0.8219]
```

Dynamic analysis of the system

```
Long-run matrix \Pi(1)-I = Po
                   LNEWS        LGDP         LPRICER
 LNEWS             -0.21253      0.088514     0.054199
 LGDP              -0.081522     0.034976    -0.0098797
 LPRICER            0.26099     -0.31579     -0.37275

Long-run covariance
                   LNEWS        LGDP        LPRICER
 LNEWS              0.14775
 LGDP               0.27321     0.76460
 LPRICER           -0.11063    -0.38872     0.26762
```

```
Eigenvalues of \Pi(1)-I
        real         complex       modulus
        -0.1441      0.0000        0.1441
         0.02291     0.0000        0.02291
        -0.4291      0.0000        0.4291


Eigenvalues of companion matrix
        real        complex       modulus
        0.8559      0.0000        0.8559
        1.023       0.0000        1.023
        0.5709      0.0000        0.5709

t-value   0.1033   0.04258    -0.2121    0.9906    -0.8331   -0.03723


             V03^2      V02*V01      V03*V01      V03*V02
Coeff.       -0.0974    0.194        -0.2433      -0.007829
t-value      -1.082     0.4787       -0.6261      -0.04616

RSS = 0.000401012  \sigma = 0.00517051
```

Model 2 Cointegration analysis 1972 to 2000

```
    eigenvalue     loglik for rank
                     279.347   0
      0.256026       283.635   1
       0.10865       285.303   2
     0.0655753       286.287   3

Ho:rank=p  -Tlog(1-\mu)  using T-nm  95%  -T\Sum log(.)  using T-nm  95%
p ==  0     8.577         7.689      21.0      13.88      12.44      29.7
p <=  1     3.336         2.99       14.1       5.302      4.754     15.4
p <=  2     1.967         1.763       3.8       1.967      1.763      3.8

standardized \beta' eigenvectors
        LNEWS        LGDP        LPRICER
         1.0000      -1.2339     -1.6228
        -5.7521       1.0000      0.26321
         4.8134      -2.8572      1.0000

standardized \alpha coefficients
 LNEWS         -0.034103     0.024635    -0.0076293
 LGDP           0.00047148   0.0054312   -0.010544
 LPRICER        0.23638      0.0039368    0.0098174

long-run matrix Po=\alpha*\beta', rank 3
                   LNEWS         LGDP         LPRICER
 LNEWS             -0.21253      0.088514      0.054199
 LGDP              -0.081522     0.034976     -0.0098797
 LPRICER            0.26099     -0.31579      -0.37275
```

Number of lags used in the analysis: 1

Variables entered unrestricted: Constant

Model 2 Estimating the model by FIML

The present sample is: **1972 to 2000**

Equation 1 for LNEWS

Variable	Coefficient	Std.Error	t-value	t-prob	HCSE
LNEWS_1	0.78747	0.13068	6.026	0.0000	0.092892
LGDP_1	0.088514	0.072595	1.219	0.2341	0.065015
LPRICER_1	0.054199	0.067408	0.804	0.4289	0.049735
Constant	-0.35328	0.50275	-0.703	0.4887	---

\sigma = 0.044611

Equation 2 for LGDP

Variable	Coefficient	Std.Error	t-value	t-prob	HCSE
LNEWS_1	-0.081522	0.063901	-1.276	0.2138	0.046441
LGDP_1	1.0350	0.035498	29.156	0.0000	0.030641
LPRICER_1	-0.0098797	0.032962	-0.300	0.7669	0.031349
Constant	-0.058922	0.24584	-0.240	0.8125	---

\sigma = 0.0218144

Equation 3 for LPRICER

Variable	Coefficient	Std.Error	t-value	t-prob	HCSE
LNEWS_1	0.26099	0.26963	0.968	0.3423	0.18451
LGDP_1	-0.31579	0.14978	-2.108	0.0452	0.12783
LPRICER_1	0.62725	0.13908	4.510	0.0001	0.16849
Constant	2.8090	1.0373	2.708	0.0120	---

\sigma = 0.0920452

Optimization result: Strong convergence

(eps1=0.0001, eps2=0.005)

loglik = 286.28658 log|\Omega| = -19.7439 |\Omega| = 2.66276e-009 T = 29

correlation of residuals

	LNEWS	LGDP	LPRICER
LNEWS	1.0000		
LGDP	0.65867	1.0000	
LPRICER	-0.28652	-0.14793	1.0000

ESTIMATION RESULTS: Model 3

Model 3. Modeling LNEWS by OLS

The present sample is: **1972 to 1987**

Variable	Coefficient	Std.Error	t-value	t-prob	PartR^2
Constant	-3.0708	0.59945	-5.123	0.0003	0.6862
LNEWS_1	0.16182	0.13708	1.181	0.2607	0.1041
LGDP	0.70459	0.10730	6.567	0.0000	0.7823
LPRICER	-0.48848	0.10196	-4.791	0.0004	0.6567

```
R^2 = 0.961263  Adj R^2 = 0.95
F(3,12) = 99.261 [0.0000]  \sigma = 0.0262712  DW = 2.34
RSS = 0.008282082806 for 4 variables and 16 observations
```

```
AR 1- 2 F( 2, 10) =     0.50927 [0.6157]
ARCH 1  F( 1, 10) =     0.15456 [0.7025]
Normality Chi^2(2)=     0.56521 [0.7538]
Xi^2    F( 6,  5) =     1.0602  [0.4846]
Xi*Xj   F( 9,  2) =     1.8093  [0.4062]
RESET   F( 1, 11) =     5.0966  [0.0453] *
```

```
Solved Static Long Run equation
       LNEWS =    -3.664             +0.8406 LGDP         -0.5828
LPRICER
(SE)          (   0.5313)          (  0.06292)          (   0.1187)

ECM = LNEWS + 3.66368 - 0.840624*LGDP + 0.582781*LPRICER;

WALD test Chi^2(2) = 182.22 [0.0000] **
```

ESTIMATION RESULTS: Model 4

Model 4. Modeling LNEWS by OLS

```
The present sample is:  1987 to 2000
```

Variable	Coefficient	Std.Error	t-value	t-prob	PartR^2
Constant	0.93453	1.1705	0.798	0.4432	0.0599
LNEWS_1	0.65868	0.32739	2.012	0.0719	0.2882
LGDP	-0.0057521	0.082379	-0.070	0.9457	0.0005
LPRICER	-0.021985	0.073787	-0.298	0.7718	0.0088

```
R^2 = 0.357055; Adj R^2 = 0.16
F(3,10) = 1.8511 [0.2017]  \sigma = 0.0316458  DW = 1.50
RSS = 0.01001459647 for 4 variables and 14 observations

AR 1- 2 F( 2,  8) =     1.0576    [0.3912]
ARCH 1  F( 1,  8) =     0.32925   [0.5819]
Normality Chi^2(2)=     3.4771    [0.1758]
Xi^2    F( 6,  3) =     0.50897   [0.7793]
RESET   F( 1,  9) =     0.0028473 [0.9586]

Solved Static Long Run equation
       LNEWS =    +2.738             -0.01685 LGDP        -0.06441
LPRICER
(SE)          (    2.329)          (   0.2394)          (   0.2516)

ECM = LNEWS - 2.73803 + 0.0168527*LGDP + 0.0644138*LPRICER;

WALD test Chi^2(2) = 0.06608 [0.9675]
```

ESTIMATION RESULTS: Model 5

Model 5. Modeling LNEWS by OLS

The present sample is: **1972 to 2000**

Variable	Coefficient	Std.Error	t-value	t-prob	PartR^2
Constant	-1.6053	0.66682	-2.407	0.0232	0.1767
LGDP	0.43938	0.061225	7.177	0.0000	0.6561
LPRICER	0.090850	0.099628	0.912	0.3699	0.0299

```
R^2 = 0.735987  Adj R^2 = 0.72
F(2,27) = 37.634 [0.0000]  \sigma = 0.0669765  DW = 0.433
RSS = 0.1211180527 for 3 variables and 30 observations
```

```
AR 1- 2 F( 2, 25) =     20.123   [0.0000] **
ARCH 1  F( 1, 25) =      2.3686  [0.1364]
Normality Chi^2(2)=      0.60878 [0.7376]
Xi^2    F( 4, 22) =      1.4021  [0.2661]
Xi*Xj   F( 5, 21) =      1.0963  [0.3917]
RESET   F( 1, 26) =     10.428   [0.0033] **
```

ESTIMATION RESULTS: Model 6

Model 6. Modeling LNEWS by OLS

The present sample is: **1972 to 2000**

Variable	Coefficient	Std.Error	t-value	t-prob	PartR^2
Constant	-0.68254	0.95268	-0.716	0.4804	0.0201
LNEWS_1	0.75573	0.12282	6.153	0.0000	0.6023
LGDPPC	0.12771	0.10627	1.202	0.2407	0.0546
LPRICER	-0.0077880	0.070543	-0.110	0.9130	0.0005

```
R^2 = 0.884955  Adj R^2 = 0.87
F(3,25) = 64.102 [0.0000]  \sigma = 0.0438776  DW = 1.80
RSS = 0.04813115193 for 4 variables and 29 observations

AR 1- 2 F( 2, 23) =      0.68494  [0.5141]
ARCH 1  F( 1, 23) =      0.023167 [0.8804]
Normality Chi^2(2)=     11.389    [0.0034] **
Xi^2    F( 6, 18) =      1.0946   [0.4029]
Xi*Xj   F( 9, 15) =      0.98915  [0.4871]
RESET   F( 1, 24) =      0.13139  [0.7202]

Solved Static Long Run equation
       LNEWS =    -2.794              +0.5228 LGDPPC      -0.03188
LPRICER
(SE)          (    3.243)          (   0.2799)          (   0.2926)

ECM = LNEWS + 2.79426 - 0.522843*LGDPPC + 0.0318832*LPRICER;
WALD test Chi^2(2) = 7.7156 [0.0211] *
```

ESTIMATION RESULTS: Model 7

Valid cases:	12
Dependent variable:	Y
Missing cases:	0
Deletion method:	None
Total SS:	0.057
Degrees of freedom:	8
R-squared:	0.989
Rbar-squared:	0.984
Residual SS:	0.001
Std error of est:	0.009
F(3,8):	229.581
Probability of F:	0.000

Variable	Standard Estimate	Prob Error	Standardized t-value	Cor with >|t|	Estimate	Dep Var
CONST	1.0960	0.4755	2.3048	0.050	---	---
LGDP	-0.0554	0.0249	-2.2221	0.057	-0.1578	-0.2363
LPRICER	-0.5424	0.1065	-5.0888	0.001	-0.3403	-0.0623
LNEWS_1	1.1391	0.0499	22.7939	0.000	0.9618	0.9668

ESTIMATION RESULTS: Model 8

Estimation of b (classical model):

Valid cases:	14	Dependent variable:	Y
Missing cases:	0	Deletion method:	None
Total SS:	0.016	Degrees of freedom:	10
R-squared:	0.357	Rbar-squared:	0.164
Residual SS:	0.010	Std error of est:	0.032
F(3,10):	1.851	Probability of F:	0.202

Variable	Standard Estimate	Prob Error	Standardized t-value	Cor with >|t|	Estimate	Dep Var
CONSTANT	0.9345	1.1705	0.7983	0.443	---	---
LPRICER	-0.0219	0.0737	-0.2979	0.772	-0.1034	0.2953
LGDP	-0.0057	0.0823	-0.0698	0.946	-0.0215	-0.2453
LNEW_1	0.6586	0.3273	2.0119	0.072	0.6451	0.5925

The posterior estimation of beta (b_ss) is:

CONSTANT 0.92439589
LPRICER -0.037296291
LGDP -0.015010957
LNEWS_1 0.70711136

Calculate the posterior Bayes estimator for the variance of the betha:

0.00023554307	3.3997129e-06	0.00016307081	5.9235226e-05
3.3997129e-06	0.0032759758	-7.5063844e-05	3.5232529e-05
0.00016307081	-7.5063844e-05	0.0094814582	4.9841717e-06
5.9235226e-05	3.5232529e-05	4.9841717e-06	0.00091871204

The posterior variance is: 0.056715140

The posterior standard deviation (std_ss) is:

CONSTANT 1.9908205
LPRICER 0.15246827
LGDP 0.15281111
LNEWS_1 0.60502893

The Baysian t-values are:

CONSTANT 0.46432911
LPRICER -0.24461674
LGDP -0.098232106
LNEWS_1 1.1687232

approximate Bayes factors:

CONSTANT 0.80937933
LPRICER 0.82018444
LGDP 0.82358701
LNEWS_1 0.71914142

ESTIMATION RESULTS: Model 9

Model 9. Modeling LNEWS by OLS

```
The present sample is:  1987 to 2000

Variable     Coefficient    Std.Error   t-value   t-prob   PartR^2
Constant     1.2476         0.18542      6.729    0.0000   0.8045
LNEWS_1      0.50575        0.074919     6.751    0.0000   0.8056
LCIRCCH      3.1119         0.29481     10.556    0.0000   0.9101

R^2 = 0.941697  Adj R^2 = 0.92
F(2,11) = 88.835 [0.0000]  \sigma = 0.00908612  DW = 2.72
RSS = 0.0009081333261 for 3 variables and 14 observations

AR 1- 2 F( 2,  9) =     1.1373 [0.3628]
ARCH 1  F( 1,  9) =     0.6347 [0.4461]
Normality Chi^2(2)=     2.406  [0.3003]
Xi^2    F( 4,  6) =     1.1202 [0.4282]
Xi*Xj   F( 5,  5) =     0.7784 [0.6050]
RESET   F( 1, 10) =     1.2118 [0.2968]

Solved Static Long Run equation
       LNEWS =    +2.524               +6.296 LCIRCCH
(SE)          (  0.01021)          (      1.06)

ECM = LNEWS - 2.52426 - 6.29623*LCIRCCH;
WALD test Chi^2(1) = 35.276 [0.0000] **
```