US Newsprint Demand Forecasts to 2020

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Abstract

The paper provides projections for US newsprint demand up to 2020. 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. This finding 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.

Key Words: *forest products, econometrics, Bayesian, long-term.*

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, 1999 a; 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; 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. However, 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). 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.[1] The most recent RPA Timber Assessment (Haynes, 2001) 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.

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[1]Although FAO (1999a, b) calls its projection model the Global Forest Products Model (GFPM), its underlying principles are the same as in PELPS model (Zhang *et al*., 1993).

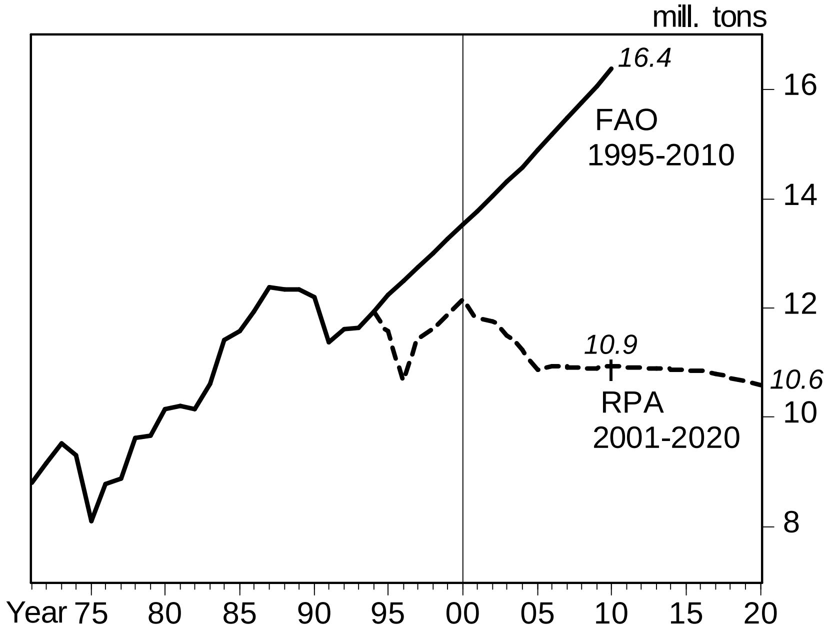

Figure 1. US Newsprint Consumption Projections: FAO (1995-2010) and RPA (2001-2020)

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, and reflects the opportunity cost. 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.

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 estimate and 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 and Buongiorno, Liu and Turner 2001). The theoretical background of the classical model is production theory, according to which the forest product enters as an intermediate input in the industry 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 as expressed in equation (1).

$$D_{ik} = a_{ik} P_{ik}^{s_{ik}} X_{ik}^{a_{s\,ik}} D_{ik,-1}^{h_{ik}}, \qquad (1)$$

where D_{ik} is the demand in *i*th 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 s, a, h are the elasticities with respect to price, GDP, and past demand (in the present case, *i* denotes US and *k* newsprint). The empirical model corresponding to (1), after taking a logarithmic transformation and using the empirical data corresponding to the theoretical variables, can be written as:

$$\ln(d_{news,t}) = a_0 + b_1 \ln(p_{news,t}) + b_2 \ln(GDP_t) + b_3 \ln(d_{news,t-1}) + e_t\,, \qquad (2)$$

where $d_{news,t}$ is the quantity of newsprint consumption in the US, $p_{news,t}$ is the real price of newsprint, GDP_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, e_t is the error term, and t is a subscript denoting the time period. Since the variables are in logarithmic form, the b -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) 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"* (p. 161). 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 (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, 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). However, to our knowledge, the genuine Bayesian estimation with informed priors has not been previously applied in forest products demand literature.[2] A number of Bayesian textbooks exist that explain the principles and differences of this approach relative to the frequentist statistical methods (e.g. West and Harrison 1997, Zellner 1971). 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

[2]Simangunsong and Buongiorno (2001) use a "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 in this paper.

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. Thus, 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 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 6 and 7 in Appendix I. As prior information, we used information that was derived from US newsprint consumption scenarios that industry experts produced in a projection exercise. Scenarios for newsprint consumption were established by the industry experts up to 2013 in 5-year intervals from 1998 onward. The methodology is described in more detail 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 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 Figure 4). 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, the 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.[3] 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.[4]

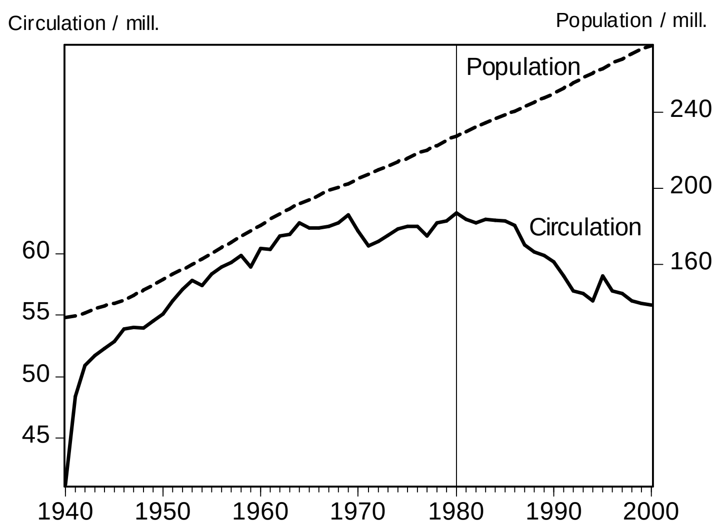

Figure 2. Newspaper Circulation Volumes and Population in US, 1940-2000

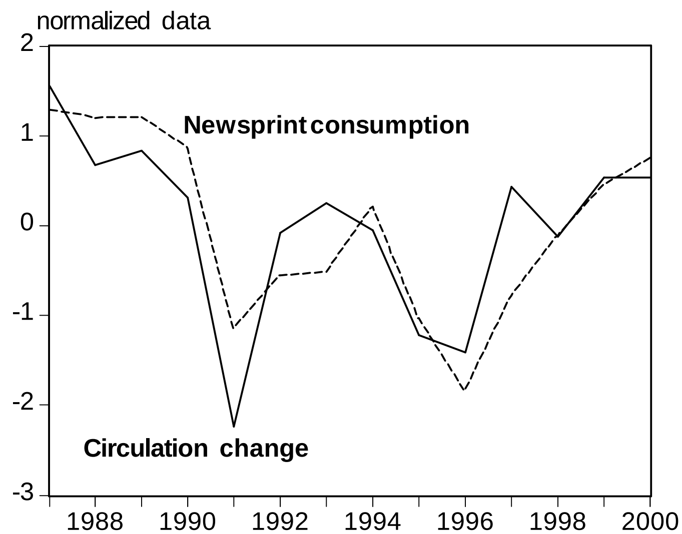

Figure 3. Newsprint Consumption and Changes in Newspaper Circulation in US, 1987-2000

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[3]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.

[4] 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.

The small sample size restricted the number of variables that could be included in the newspaper circulation model. Thus, besides the constant term and the newspaper circulation variable, only the lagged newsprint demand variable was included. The lagged dependent variable allows some dynamics, which is often necessary to avoid autocorrelation. On the basis of the above reasoning, the following model to forecast newsprint demand was formulated in logarithmic form:

$$\ln(d_{news,t}) = g_0 + g_1 \Delta \ln(circ_{news,t}) + g_2 \ln(d_{news,t-1}) + m_t \tag{3}$$

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, m_t is the error term, and t is a subscript denoting the time period. We would expect the g_1-parameter to have a positive sign, since an increase (decrease) in the circulation should cause an increase (decrease) 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.[5] The various cointegration test results pointed to the possibility of either zero or one cointegration relationship between the three variables in the classical model (for details, see Hetemäki and Obersteinr 2001). The newspaper circulation change series is on the border of being a I(0) 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 suggests 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). We chose 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.[6] 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.

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

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

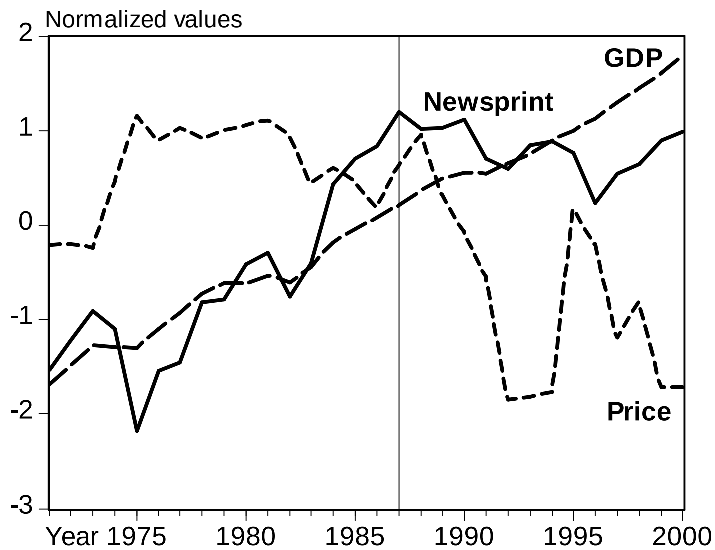

Figure 4. US Newsprint Consumption, Real GDP, and Real Newsprint Price, 1971-2000

Table 1. Correlation Coefficients

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

5.2 Classical Model

Due to the structural break in the data, estimations of the classical model (eq. 2) 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.

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 (the detailed estimation results can be obtained from the authors).[7]

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.

[7]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.

Table 2 Estimation Results

MODEL *estim. period*	Const	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***	1.60 (1.68)	0.08 (1.01)	0.33	-0.02 (0.21)	-0.06	0.77 (6.09)		0.87	No
2. Classical VAR (1st Order) ***1971-2000***	0.87 (0.94)	0.12 (1.84)	0.46	0.07 (1.12)	0.27	0.74 (6.17)		0.87	No
3. Classical ***1971-1987***	4.97 (4.90)	0.70 (6.57)	0.84	-0.49 (4.79)	-0.58	0.16 (1.18)		0.95	No
4. Classical ***1987-2000***	3.34 (1.05)	-0.01 (0.14)	-0.04	-0.03 (0.46)	-0.11	0.68 (2.07)		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 (0.59)	0.03 (0.43)	0.13	-0.01 (0.02)	-0.01	0.74 (5.42)		0.55	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 (6.73)					0.51 (6.75)	3.11 (10.56)	0.92	No

* t-values in parentheses

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 5 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.

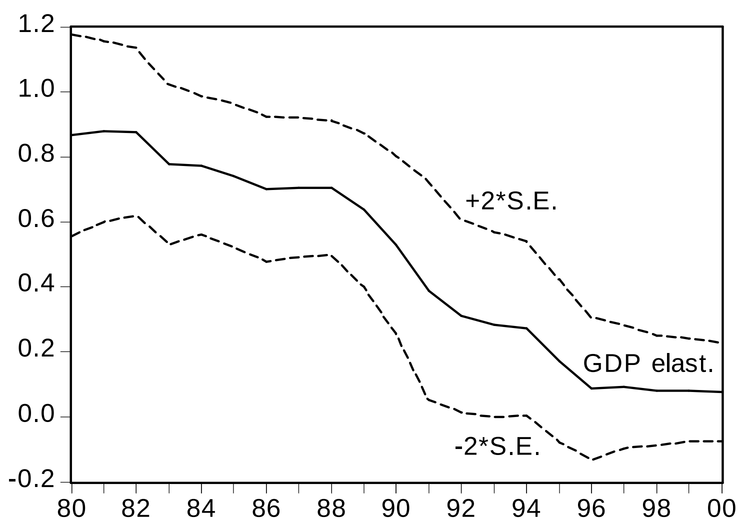

Figure 5. Recursive Coefficient Estimates for GDP (Model 1)

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. 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.

The forecast results for 2010 and 2020 are shown in Table 3. First, the FAO (1999a) and RPA (Haynes, 2001) projections are shown.[8] 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).

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%. A graph, not presented here, showed that projections from FAO model, Model 1, and Model 2 extrapolate the pre-1987 historical trend, while 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. Both the GDP and newsprint price variable turn out to be statistically insignificant determinants of newsprint consumption, when post-1987 data is used to estimate the classical model.

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), the second moment of the GDP elasticity of the expert model as an informed prior was used. 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.[9]

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 (i.e. Model 4), shows that the estimates and forecasts are very similar between these two approaches. This

[8]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”.

[9] Due to this assumption the information contained in the second moments were not directly used as priors for $\mathbf{H}^*$. 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.

implies that using the expert information (prior) does not really change the frequentist classical model projections. Thus, the experts views in the present case seem to reflect the implications of the recent 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. 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. This would also allow the introduction of model uncertainty, i.e., the uncertainty related to the choice of the regressors. Thus, we could also specify a prior distribution over the model space (Fernandez *et al.* 2001).

5.4 Newspaper Circulation Model

The newspaper circulation model (equation 3) was estimated using data for the period 1987–2000. The estimation results 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 available from the authors). 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), 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*" (p. 4). The study also reports evidence that the two phenomenon 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.[10]

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

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

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.

The dynamic forecasts of the newspaper circulation model (Model 9) based on the above assumptions are shown in Figure 6. 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.

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 6 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 RPA model (Haynes 2001), Model 4, and the Bayesian models (Models 7 and 8) are similar. These projections indicate a slight decline in newsprint consumption from today's level when moving towards 2020. Interestingly, the forecasts of Model 8, which are based on industry expert information, are lower than Model 4 forecasts, which are based purely on time-series evidence. Thus, industry experts expect slightly larger decline in newsprint consumption than recent historical data would imply. 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 projects 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.

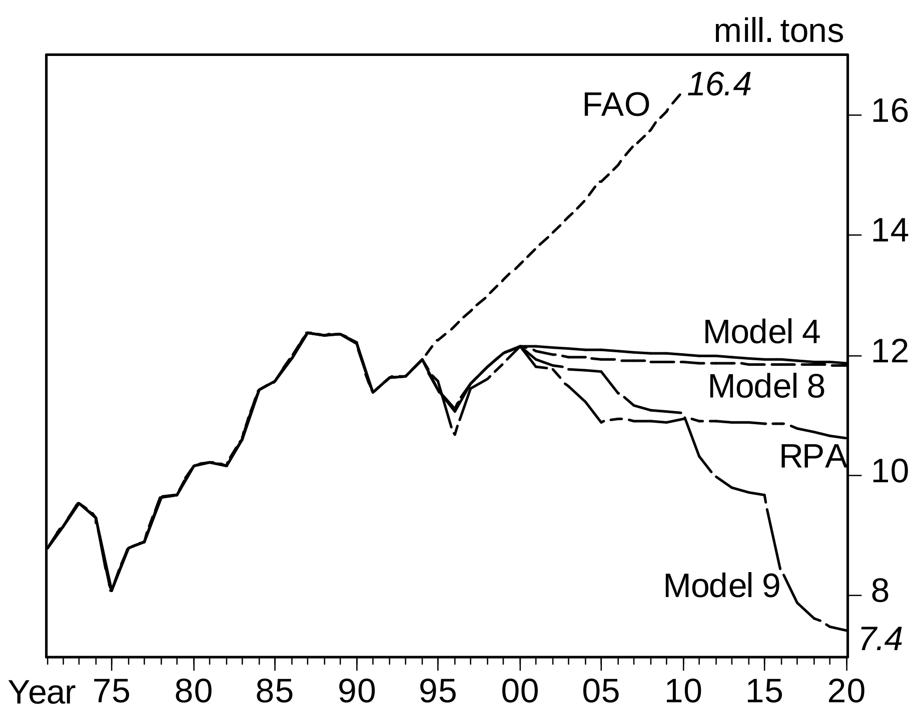

Figure 6. Forecasts from Various Models

From the practical policy perspective, the differences in the projections are significant and troubling. Depending on whether the 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. FAO projection would imply more or less the "business-as-usual" pattern for the newsprint industry, while Model 9 projection would imply major cuts in domestic production and imports.

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

6. Summary and Conclusions

The results indicated that the classical forest products demand model, still commonly used in the 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 indicate that one should not rule out the possibility of a negative income elasticity, although it is usually interpreted to be inconsistent with the demand theory and reflect an error in the model, estimation, or data. 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 related to the classical newsprint demand model, two alternative approaches were proposed – 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. It presented a methodology that allows forest sector analysts to incorporate the 'future' into 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 the model. 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.

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Appendix I: The Bayesian Normal-Gamma Regression Model

Consider the linear regression model

$$Y_t = x_t' b + u_t$$

where $u_t \approx i.i.d.N(0, s^{2})$, x_t is a (kx1) vector of exogenous explanatory variables, and b 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. s^{2} and b are both regarded as random variables. The prior distribution for s^{2} is given by the gamma distribution. Instead of describing the prior distribution in terms of the variance s^{2} it is convenient take the reciprocal of the variance, s^{-2}, which is known as the precision:

Equation 1

$$f(s^{-2}|X) = \frac{\left(l^{*}/2\right)^{N^{*}/2} s^{-2\left[\left(N^{*}/2\right)-1\right]} \exp\left[-l^{*} s^{-2}/2\right]}{\Gamma\left(N^{*}/2\right)}$$

where N^{*} and l^{*} are parameters that describe the analyst's prior information. The prior distribution of b conditional on the value for s^{2} is given by

Equation 2

$$f(b|s^{-2}, X) = \frac{1}{(2ps^{2})^{k/2}} \left|H^{*}\right|^{-1/2} \exp\left\{\left(-\frac{1}{(2s^{2})}\right)\left(b - b^{*}\right)' H^{*-1}\left(b - b^{*}\right)\right\}$$

Thus, prior to observation of the sample, the analyst's best guess for the value of b 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, $f(b, s^{-2}|X)$, the joint prior density for b and s^{2}, is given by the product of (
Equation 1) and (

Equation 2). The posterior distribution $f(b, s^{-2}|y, X)$ is described by the following proposition.[11]

Proposition[12]: *Let the prior density* $f(b, s^{-2}|X)$ *be given by the product of (*

[11] see Hamilton (1994), p. 356-57

Equation 1*) and (*

Equation 2*), and let the sample likelihood be*

Equation 3

$$f(y|b, s^{-2}, X) = \frac{1}{\left(2ps^{2}\right)^{T/2}} \exp\left\{\left[\frac{1}{2s^{2}}\right]\left(y - Xb\right)'\left(y - Xb\right)\right\}.$$

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

Equation 4

$$f(b, s^{-2}|b, X) = f(b|s^{-2}, y, X) \cdot f(s^{-2}|y, X)$$

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

Equation 5

$$f(b|s^{-2}, y, X) = \frac{1}{(2ps^{2})^{k/2}}\left|H^{*}\right|^{-1/2} \exp\left\{\left(-\frac{1}{(2s^{2})}\right)\left(b - b^{**}\right)' H^{**-1}\left(b - b^{**}\right)\right\}$$

with

Equation 6

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

Equation 7

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

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

Equation 8

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

with

Equation 9

---

[12] For a proof see Hamilton (1994), p.367-69.

$$N^{**} = N^{*} + T$$
$$l^{**} = l^{*} + (y - Xb)'(y - Xb) + (b - b^{*})' H^{*-1} (X'X + H^{*-1})^{-1} (b - b^{*})$$

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

The Bayesian estimate of the precision is then given by,

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

For more detailed description for the Normal-Gamma regression model see e.g. Hamilton (1994) or Zellner (1971).