

Testing for input separability in the Canadian CATV industry: An application of generalized additive mixed models

ABSTRACT

The nature of input relationships has important consequences for regulatory policy since the impact of rate-of-return regulation depends on the extent of substitution offered by production technologies adopted by regulated firms. The use of classical regression analysis has been criticized for various reasons (e.g., the linearity of regression functions in predictors, the fixed-variance premise of the response across sample observations, the *i.i.d.* postulation of the random error terms in addition to their normal distribution, and non-complying data in real cases) which might lead to inappropriate policy recommendations. Earlier research suggested an alternate approach involving generalized additive models (GAMs) that do not have the problems that confront classical analysis; however, in the presence of complex covariate effects between data series, the use of generalized additive mixed models (GAMMs) is recommended. GAMMs encompass generalized linear mixed models (GLMMs) and GAMs as special cases. A GAMM is a non-*ad hoc* generalization of a GLMM except that an additive unknown combination of nonparametric functions of covariates and random effects replace the predetermined linear predictor in GLMM. Using GAMMs, we develop a nonparametric cost function. First, we estimate the model parameters using general spline smoothing techniques. Second, we apply residual deviance analysis to test separability and complementarity between the inputs. We use an unbalanced panel of operating data from regulated Canadian cable television (CATV) firms, examining the period from 1990 to 1996 because CATV was a rate- and entry-regulated industry prior to 1997. This study also suggests avenues for research in other regulated industries.

Keywords: Generalized additive mixed models, generalized additive models, spline smoothing, input separability, Canadian cable television industry.

JEL Codes: C13, C14, L51.

1. INTRODUCTION

One of the most challenges that researchers face in applied microeconomics is to identify the nature of relationship (i.e., substitutability/complementarity) amongst inputs used in the production process. For instance, in a noncompetitive market structure the knowledge of input substitutability would provide sufficient incentives for producers to integrate with their customers [1]. However, the outcome of this integration will entirely depend on the type of market structure. If, for example, monopoly is the dominant type of market structure it is unknown whether such integration increases the industry output or reduces the total final production. An important concept in production theory is output elasticity that is defined as the percentage change in input usage for one per cent change in output level when input prices are held constant [2]. It is important for researchers to know how sensitive total production is with respect to a change in the price of an input. When inputs are perfect complements, all variable inputs are output elastic [3]. This means that for a given level of output, marginal cost will raise

in a rate more than average cost for an increase in input price. Moreover, precedent studies showed that complementarity characteristics of factors of production could help downstream firms purchase intermediate goods from various wholesale markets to make their own final products [4]. One of the industries that usually gain from complementary characteristics of inputs is the information and communication technology sector where knowledge-based factors of production are used in combination with each other. The supermarket industry is another example that offer bundle products to reduce their customers' acquisition costs. As a result, testing relationships amongst inputs used in the production process would have particular policy relevance for many industries including the Canadian cable television (CATV) industry because, given the substitutability/complementarity of an input with respect to other factors of production, the rate of return regulation can take different forms [5]. This challenge becomes much bigger when classical regression analysis is used to estimate the parameters of the production/cost function in econometric models. It has been a general consensus among practitioners for a long time that classical regression analysis would have been a good method of estimating the parameters of regression functions in applied studies. In spite of being widely used, however, this method of analysis is not without major drawbacks. Classical regression analysis has been criticizing for various reasons (e.g., the linearity of regression functions in predictors, the fixed-variance premise of the response across sample observations, the *i.i.d.* postulation of the random error terms in addition to their normal distribution, and uncomplying data in real cases) which might lead to lose the validity of these types of models [6]. Alternatively, precedent studies suggested the use of generalized additive models (GAMs), proposed by [7] that do not have the aforementioned problems; however, the use of GAMs is not recommended in the presence of complex covariate effects between data series. Instead, under these circumstances literature suggests a broader methodology, known as the generalized additive mixed models (GAMMs), suggested by [8], which is a non-*ad hoc* extension of generalized linear mixed models (GLMMs) except that an additive unknown combination of nonparametric functions of covariates and random effects replace the predetermined linear predictor in GLMM. A GAMM encompasses GLMMs and GAMs as special cases.

To our knowledge no studies are available in the literature to examine input relationships (i.e., substitutability/complementarity) in the Canadian CATV industry where correlation amongst covariates is predicted. In this paper, we use the theory of GAMMs and develop a nonparametric cost function to test input separability amongst factors of production used in the model. First, we estimate the GAMM model parameters using general spline smoothing techniques. Second, we apply the residual deviance analysis [9] to test either substitutability or complementarity amongst the factors of production. To do this, we utilize an unbalanced panel of operating data collected from the regulated CATV firms between 1990 and 1996. This period is of particular interest to policymakers because the Canadian CATV was a rate- and entry-regulated industry prior to 1997.

The rest of the paper is organized as follows. Section 2 briefly presents a theoretical aspect of GAMMs and demonstrates the residual deviance statistic test used to examine relationships amongst input used in the model. Section 3 provides the empirical results and the final section concludes the study and outlines directions for further research.

2. GENERALIZED ADDITIVE MIXED MOELS

2.1 Model Specification

Generalized additive mixed models (GAMMs) are nonparametric extensions of generalized linear mixed models (GLMMs) of [10]. A GLMM is an extension of a generalized linear model [11] in which covariate effects are modeled by a parametric mean function through inclusion of random effects to the linear predictor to estimate the parameters of the econometric model with overdispersed and correlated outcomes. Generalized linear mixed models have been used widely in different fields, including clinical trials and disease mapping, longitudinal studies, survey sampling, fisheries and aquaculture, etc. [8,10,12,13]. The use of GLMM, however, is not without drawbacks. The shortcoming of the GLMMs, similar to other parametric econometric functions, relates to the prespecified functional form of the mean parametric function that is used to model covariate effects. The knowledge of the true functional form is always unknown to researches, and, as a result, the outcome variable would be varied had different functional forms been selected. To circumvent the aforementioned problem, GAMMS was proposed by [8], which are basically nonparametric regression models with an unspecified nonparametric mean function that can be incorporated into the GLMMs to provide more flexibility and mitigate the dependency of outcome variable on the covariates.

Following the prominent work of [8], a brief explanation of GAMMs follows. Consider a standardized multiple regression function with a series of predetermined random or non-random m explanatory variables (covariates) $x_i = [1, x_{i1}, \dots, x_{im}]'$ associated with fixed effects and a $w \times 1$ vector of predictors q_i independent variables associated with random effects that projects collectively variations in the response (dependent variable) y_i with i^{th} number of observations from n unit of firms. Assuming y_i to be conditionally and independently distributed with the expected values of $E(y_i|c) = \mu_i^c$ where c consists of $w \times 1$ vector of random effects and variances $var(y_i|c) = \delta g_i^{-1} \sigma(\mu_i^c)$ that follow a GAM of which $\sigma(\cdot)$ shows a predetermined variance function, g_i is a specified weight, such as a binomial denominator, and δ represents a scale parameter. Given the above expressions, equation (1) specifies a GAMM:

$$s(\mu_i^c) = \gamma_0 + f_1(x_{i1}) + f_2(x_{i2}) + \dots + f_m(x_{im}) + q_i'c \quad (1)$$

in which $s(\cdot)$ shows a twice differentiable monotonic link function, $f_j(\cdot)$ represents a smooth function that is twice-differentiated, c , i.e., the random effects are assumed to be normally distributed with zero mean and variances $V(\emptyset)$ where $\emptyset$ is a $d \times 1$ vector of variance components [8]. The key element of equation (1) is that there is no *a priori* on the type of relationship between response and the covariates. For instance, if it is linear, i.e., $f_j(\cdot)$ are linear functions, then equation (1) changes to GLMMs. Under ordinary circumstances, the nonparametric functions are used in equation (1) to express relationships amongst covariate effects, and correlation among the sample data are modeled by the random effects component of equation (1). According to [8] statistical inference in equation (1) includes (i) the estimation of the nonparametric functions $f_j(\cdot)$, which, in turn, depends upon the choice of span degree, also known as the smoothing parameter [6], and (ii) the estimation of the variance component, $\emptyset$, by using the marginal quasi-likelihood method. Interested readers can find more about different derivation of equation (1) in [14,15].

2.2 Statistical Inference

An inherent assumption in GAMMs is that covariates are additive separable. It was argued that the concept of additively separable of the covariates in a production process might not be always true [16]. When using either GAMs or GAMMs, it is recommended to examine additive separability of the covariates [6,17]. To do this, the use of the residual deviance analysis was suggested, which is simply the logarithm of the likelihood ratio (LR) that follows a chi-squared distribution [9]. Equation (2) shows how the value of the deviance is obtained from taking the differences between the restricted and unrestricted LR statistic tests. In particular, the computed value of deviance, $\hat{\rho}$

$$Devi(s; \hat{\rho}) = -2\{l(\rho; s) - l(\rho_{max}; s)\} \quad (2)$$

in which $l(\rho; s)$ and $l(\rho_{max}; s)$, respectively, represent the values of the unrestricted and restricted LR. In equation (2), $Devi(s; \hat{\rho})$ has a degree of freedom approximately equal to the differences in the dimensions between the two restricted and unrestricted models, which is the principle of examining input separability in this article [7].

3. EMPIRICAL ANALYSIS

To examine input relationships (i.e., substitutability/complementarity) amongst factors of production in our econometric model, we utilized the same dataset used in [18], which was collected from the Canadian CATV industry between 1990 and 1996. The data were recorded annually by the Canadian Radio-television Telecommunication Commission (CRTC); an authorized organization for regulating the cable television during the period of the study in Canada. According to [19], the CRTC has divided Canada into several zones, so-called licensed service areas (LSAs), and given exclusive rights to cable television firms throughout the entire country. The data included an unbalanced panel data of 1,041 observations related to the 242 unique undertaking identification (UID) codes for Canadian cable providers during the period of the study. Each UID code was allotted to only one LSA showing the number of individual cable operations in the sample. Thus, each LSA in the data was assumed to be one unit of CATV service production. Assuming that the duality premise holds [20], we specified a nonparametric cost function within a GAMM framework and used the statistical program, known as *R* (version 2.12.1.) to estimate the parameters of the model using general smoothing techniques.

Table 1 shows the statistical description of the variables used in the model. The dependent variable is the total cost, which is computed as the summation of total operating expenses and the user cost of capital for all subscribers of which the operating expenses include the cost of labor the difference between total expenses and those outlays paid for programming. The independent variables or covariates of the model consist of the total number of basic and non-basic cable subscribers as output and the prices of labor, capital, and materials as applied to the industry. The data for each of the covariates is separately calculated for both the basic and non-basic cable subscribers. The first group of subscribers receive core channels, arranged by the CATV operator that local television stations would normally broadcast. The non-basic subscribers receive more channels (e.g., movie, documentary, sports) than the first group do by paying extra money for

each tier. Total payments made to all employees, who provided services for both the basic and non-basic subscribers within each of the LSAs were divided by the number of employees that yielded the price of labor [18]. The summation of depreciation and financial rates was used to obtain the rental price of capital. We refer interested readers to find more about the calculation of the price of capital in [18]. Finally, the price of materials was obtained by computing the per unit expenditure on intermediate inputs. To do this, [18] spread total costs, excluding those payments made for labor and capital, over a per cable kilometer and per channel basis for all subscribers during the period of the study. To lessen any possible heteroskedasticity in the data, all variables were calculated per unit of output and transformed to logarithms.

Table 1. Statistical description of the variables

Variable	Mean	S. D.	Min.	Max.
Total Costs (\$ 000)	6,975.3	16,533.7	30.6	222,821.3
Price of Labor Shared in Basic Subscribers (\$)	40,388.3	16,275.1	487.6	163,872.6
Price of Labor Shared in Non-Basic Subscribers (\$)	30,790.8	18,458.6	90.3	177,500.0
Price of Capital Shared in Basic Subscribers	0.3211	0.2604	0.1267	7.6618
Price of Capital Shared in Non-Basic Subscribers	0.6045	1.3354	0.1202	40.8860
Price of Material Shared in Basic Subscribers (\$/km 000 per channel)	181.4	128.9	15.1	1,872.6
Price of Material Shared in Non-Basic Subscribers (\$/km 000 per channel)	161.3	143.6	10.2	1,655.9
Number of Basic Subscribers	28,004.0	58,747.0	91.0	586,606.0
Number of Non-Basic Subscribers	19,581.0	51,744.0	14.0	573,420.0

Source: Sample data. Data also used in [18].

Using equation (1), we estimated the nonparametric cost function, specified in a GAMM, using the spline smoothing techniques. We call this specification as the restricted model and its estimation results are shown in Table 2.

Table 2. Estimation results from GAMMs (restricted model)

Predictors	Estimates	Est. Error	Non-parametric <i>t</i> -value	<i>p</i> -value
Fixed Effects:				
Intercept	14.642	0.0062	2347.374	0.0000
Price of labor shared in basic subscribers	-7.293	10.435	-0.6989	0.4848
Price of labor shared in non-basic subscribers	-0.276	0.1163	-2.3767	0.0177
Price of capital shared in basic subscribers	-0.265	0.3317	-0.7996	0.4242
Price of capital shared in non-basic subscribers	16.822	10.682	1.5748	0.1157
Price of material shared in basic subscribers	-6.046	15.923	-0.3797	0.7042
Price of material shared in non-basic subscribers	0.131	0.1697	0.7769	0.4374
Number of basic subscribers	0.447	0.0908	4.9270	0.0000
Number of non-basic subscriber	-5.666	16.0348	-0.3534	0.7239
Log-likelihood	211.6733	BIC		-300.9235
AIC	-387.3466	Number of observations		899
Degrees of Freedom	18			

Source: Sample data. Data also used in [18].

The computed values of the log-likelihood and the Akaike Information Criterion are 211.67 and 388.67 (in absolute value), respectively. Among all the coefficients of the model (except the intercept) the price of labor shared in non-basic subscribers (*p*-value 0.0177), the number of basic subscribers (*p*-value 0.000), and the price of capital shared in non-basic subscribers (*p*-value 0.1157) were statistically significant. To check if our estimated cost function, defined in equation (1), conforms to the inherent premise of additive separability of the covariates in the model we utilized the statistical test described in equation (2). This means that we examined if a change in one of the input prices could have any impact on the dependent variable, i.e., total cost, through the total numbers of basic and non-basic subscribers. In particular, we wanted to know if changes in the wage rates shared by basic services have any impact on the total cost of providing services for non-basic subscribers. Furthermore, we tested whether or not total cost changes as a result of a change in the rental price of capital shared by basic services through non-basic subscribers. To do this, we specified two unrestricted nonparametric cost functions and estimated the parameters of the models using the same methodology as the restricted model was estimated.

Table 3 presents the estimation results of the first unrestricted model in which a new variable was obtained from the product of the price of labor shared in basic subscribers and the

number of non-basic subscribers. We hypothesized that if the number of non-basic subscribers changes it might affect the amount of labor hired in basic subscribers, which in turn, might change the total cost of operations. The computed value of the log-likelihood is 214.05 and the Akaike Information Criterion (in absolute value) is 388.10. The coefficient of the rental price of capital shared in non-basic subscribers was statistically different from zero (p -value 0.000) with 99 per cent confidence. The new variable (i.e., the interaction between the number of non-basic subscribers and the wage rates shared in basic subscribers) was not statistically significant (p -value 0.276).

Table 3. Estimation results from GAMMs (unrestricted model)^a

Predictors	Estimates	Est. Error	Non-parametric <i>t</i> -value	<i>p</i> -value
Fixed Effects:				
Intercept	14.642	0.0061	2383.0539	0.0000
Price of labor shared in basic subscribers	-4.095	10.9623	-0.3736	0.7088
Price of labor shared in non-basic subscribers	-9.909	8.0792	-1.2266	0.2203
Price of capital shared in basic subscribers	-0.253	0.3282	-0.7716	0.4406
Price of capital shared in non-basic subscribers	13.379	11.2192	1.1925	0.2334
Price of material shared in basic subscribers	-23.175	21.3500	-1.0855	0.2780
Price of material shared in non-basic subscribers	0.151	0.1699	0.8940	0.3716
Number of basic subscribers	0.437	0.0905	4.8362	0.0000
Number of non-basic subscriber	-0.606	16.8540	-0.0360	0.9713
Product of the number of non-basic subscribers & price of labor in basic subscribers	-21.308	19.5545	-1.0897	0.2761
Log-likelihood	214.0513	BIC	-292.0769	
AIC	-388.1026	Number of observations	899	
Degrees of Freedom	20			

Source: Sample data. Data also used in [18].

^aThe interaction term is obtained from the product of the number of non-basic subscribers and the price of labor in basic subscribers.

The estimation results of the second unrestricted model are shown in Table 4 in which an interaction term was defined as the product of the price of rental capital shared in basic subscribers and the number of non-basic subscribers. We intended to examine if, for instance, the number of non-basic subscribers increases, the total operation costs would also be increased due to the changes in the amount of labor needed to be hired for basic subscribers. The calculated value of the log-likelihood is found to be 212.47 and the Akaike Information Criterion equals 384.49 in absolute value. Among all the coefficients of the model (except the intercept), the price of labor shared in non-basic subscribers (p -value 0.0203) and the number of basic subscribers (p -value 0.000) were statistically different from zero. The coefficient of the new covariate (i.e., the interaction between the number of non-basic subscribers and the rental price of capital shared in basic subscribers) was not statistically significant (p -value 0.285).

Table 4. Estimation results from GAMMs (unrestricted model)^b

Predictors	Estimates	Est. Error	Non-parametric <i>t</i> -value	<i>p</i> -value
Fixed Effects:				
Intercept	14.642	0.0062	2347.5286	0.0000
Price of labor shared in basic subscribers	-3.865	10.9229	-0.3539	0.7235
Price of labor shared in non-basic subscribers	-0.271	0.1164	-2.3256	0.0203
Price of capital shared in basic subscribers	8.674	8.3712	1.0362	0.3004
Price of capital shared in non-basic subscribers	13.301	11.1849	1.1893	0.2347
Price of material shared in basic subscribers	-21.833	21.6913	-1.0065	0.3144
Price of material shared in non-basic subscribers	0.114	0.1720	0.6677	0.5045
Number of basic subscribers	0.444	0.0908	4.8881	0.0000
Number of non-basic subscriber	-0.331	16.8042	-0.0197	0.9843
Product of the number of non-basic subscribers & price of capital in basic subscribers	-20.875	19.5312	-1.0688	0.2854
Log-likelihood	212.2478	BIC	-288.4700	
AIC	-384.4957	Number of observations	899	
Degrees of Freedom	20			

Source: Sample data. Data also used in [18].

^bThe interaction term is obtained from the product of the number of non-basic subscribers and the price of capital in basic subscribers.

It is a general consensus that the incorporation of the interaction term would add more information to the specified model. This implies the initial pair of covariate is not expected to be additive separable. By simply applying the likelihood ratio (LR) statistic test (i.e, equation 2), we examined the null hypothesis of separability amongst additive predictors used in the model. For each of the unrestricted model, we conducted the LR test. Table 5 presents the results of statistical inference obtained from examining the null hypotheses. The computed values of deviance for both models were 4.7559 (model 1) and 1.1490 (model 2), which were less than the critical value of the chi-squared distribution (3.84) with 95 per cent confidence and one degree of freedom. Thus, the interaction term in both models was not statistically different from zero implying that the addition of the new covariate to the primal nonparametric cost function (restricted model) would not be necessary as it did not add any more information to the model. As a result, the additive separability assumption between covariates for cost estimation in the CATV industry is valid.

Table 5. Statistical Inference from comparing the restricted and unrestricted GAMMs

New Predictor	DF ^a	Deviance Value	<i>p</i> -value
Model 1:			
Non-basic subscribers & Price of labor shared in basic subscribers	20	4.7559	0.0927
Model 2:			
Non-basic subscribers & Price of capital shared in basic subscribers	20	1.1490	0.5630

Source: Source: Sample data. Data also used in [18].

^a Degrees of freedom

In summary, the result of this study helps policymakers make proper decisions for the industry. As it was argued, the concept of input separability could show how the marginal rate of technical substitution (MRTS) would be changed by any alterations made in other covariates through a third dimension [5]. For instance, if the demand for capital for basic CATV services changes as a result of a change in the number of employees hired for non-basic subscribers, the total operational costs would not be changed. Nevertheless, it is very important for stakeholders in the industry to know which one of the covariates is separable from statistical perspective in the production process. If this piece of information is available then suitable status is provided for firms to make informed decisions.

4. CONCLUSION AND OUTLOOK

Whether a factor of production has a substitute or complementarity relationship with other inputs used in the production process is a valuable knowledge for policymakers. Policymakers are interested in understanding better such relationship because it affects the rate of return

regulation. Prior to the development of nonparametric and semiparametric regression analyses, the most widely used method of estimating the parameters of model was the classical regression analysis. This type of quantitative analysis, however, has been undergoing criticisms for its rigidity on prespecified presumptions, axioms, and postulations. To work with a relatively non-ad hoc method of regression analysis econometricians suggest the use of the generalized additive models and generalized additive mixed models. However, in the presence of complex covariate effects between data series, the use of the former models is not recommended. These groups of models can be estimated using a series of iterating and smoothing techniques such as the backfitting algorithm, generalized spline smoothing approaches, and the locally weighted scatterplot smoothing [5]. This paper demonstrates one of the applications of the generalized additive mixed models in examining input relationships (i.e., substitutability/complementarity) in the Canadian cable television industry; a rate- and entry-regulated industry prior to 1997. The result of this study showed that the industry was characterized by separable factors of production during 1990 to 1996. The cable television industry in Canada is using a highly labor savings type of technology. In addition, the findings of the research help policymakers to have an in-depth understanding of such a network-based industry and its current nature of providing services in the country.

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