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Essays on food demand analysis

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Abstract

The main objective of this thesis is to investigate the demand for food products from the producer and health perspectives. The thesis consists of five essays that explore Norwegian consumers' reactions to changes in prices of food products, and the effects of income, advertising, health information, and food scares. In the first essay, the main conclusion is that information on mad cow disease (BSE) did not change beef consumption in Norway. This result may be explained by the fact that no BSE cases were detected in Norway and, moreover, that consumers trusted the producers and controlling authorities. The second essay investigates the effects of advertising on milk demand. The conclusion is that, although milk advertising has a positive effect on total milk demand, such advertising is not profitable for producers. The third essay explores different methods for making forecasts of demand for food products, specifically dairy products. In the fourth essay, the demand for carbonated soft drinks containing sugar is investigated. From a public health perspective, the demand from high-consuming households is more important than the average demand. The main conclusion in essay four is that an increase in the taxes on carbonated soft drinks will lead to a small reduction in consumption by households with a small or moderate consumption and a huge reduction in households with a large consumption. In the fifth essay, the problem is the opposite. An increase in the demand for vegetables by low-consuming households is more important than an increase in the average demand. It is shown that the removal of the value added tax for vegetables, increases in income, and increases in health information are unlikely to substantially increase vegetable purchases by low-consuming households. Nevertheless, information provision is cheap and may be well targeted at low-consuming households.

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Contents

Introduction

Introduction

The thesis consists of five essays on food demand analysis. They are based on neoclassical consumer theory and the econometric estimation of demand functions. The essays can be read separately; however, thematically as well as empirically they are closely related. Three essays have been published in scientific journals and three essays are coauthored with Kyrre Rickertsen.

The essays are:

Essay 1: The BSE Crisis and the Reaction of Norwegian Consumers, by Geir Wæhler Gustavsen. Published in *Cahiers d'Economie et Sociologie Rurales* 50 (1999): 22–34.

Essay 2: Fluid Milk Consumption and Demand Response to Advertising for Non-Alcoholic Beverages, by Kyrre Rickertsen and Geir Wæhler Gustavsen. Published in *Agricultural and Food Science in Finland* 11 (2002): 13–24.

Essay 3: Forecasting Ability of Theory-Constrained Two-Stage Demand Systems, by Geir Wæhler Gustavsen and Kyrre Rickertsen. Published in *European Review of Agricultural Economics* 30(4) (2003): 539–558.

Essay 4: Public Policies and the Demand for Carbonated Soft Drinks: A Censored Quantile Regression Approach, by Geir Wæhler Gustavsen.

Essay 5: A Censored Quantile Regression Analysis of Vegetable Demand: Effects of Changes in Prices, Income, and Information, by Geir Wæhler Gustavsen and Kyrre Rickertsen.

This chapter gives a brief presentation of the essays and summarizes the results. First, the objectives of each essay are presented. Second, important parts of the existing literature are reviewed. Third, a summary of each essay is provided. Fourth, some similarities and differences between the essays are discussed. Finally, the contributions of the thesis are summarized.

Objectives

The thesis analyzes various aspects of the demand for food and beverages. The producer perspective is the focus of three of the essays, and public concerns regarding health and nutrition are the focus of the other two.

I start by analyzing the demand for dairy products and beef. The analysis is of primary importance for producers; however, the results also have implications for regulating authorities. In essay one, I study the effects of information on mad cow disease (BSE) on beef demand. In essay two, we study the effects of advertising on the demand for fluid milk. In essay three, we investigate how to make forecasts for food products, specifically dairy products. The results in these essays are of importance to beef and dairy farmers and their marketing organizations, which need to forecast the demand given changes in exogenous variables. Furthermore, a forecasting model is a useful tool for the regulating authorities that set target prices for dairy products. The model may also be useful in analyzing the effects of changes in the import regime caused by, for example, negotiations by the World Trade Organization (WTO). Furthermore, dairy farming is an important component of Norwegian rural policy. Dairy farms are mainly situated in rural areas where they contribute to jobs in agricultural as well as other sectors.

In essay four, I analyze the demand for carbonated soft drinks containing sugar. High consumption of sugar is not beneficial from a public health perspective and the health authorities want us to decrease the consumption of sugary soft drinks. In essay five, the problem is the opposite. High consumption of vegetables is beneficial and the public authorities want to increase the consumption. Various public policies could achieve such objectives. One possibility is through price interventions by, for example, changing the value added tax (VAT). Another policy instrument is health information, which also may be effective in changing consumption. Finally, income changes will alter the composition of consumption, in a healthy or less healthy direction. Typically, the mean effects of changes in such variables have been investigated. However, from a public health perspective, the effects on high- or low-consuming households may be of more interest. Increasing vegetable consumption among households consuming large quantities will increase the average consumption but may not substantially improve public health. Increasing the consumption among the low-consuming households is more important. Correspondingly, when studying sugary soda consumption, it is important to reach the target households; i.e., the high-consuming households. To estimate the effects of policy changes at the tails of the consumption distribution, we use quantile regressions. At the lower quantiles, censoring is a major problem and we use censored quantile regression. This method has rarely been used to study food demand.

Literature Review

The thesis is based on neoclassical consumer theory and the estimation of demand functions. The first person to apply theory consistently to define and modify demand equations was Stone (1954a), who estimated price and income elasticities for 48 categories of food consumption from British data. Further attempts to impose structure on demand equations were made by Stone (1954b), who developed the linear expenditure system, and by Theil (1965) and Barten (1966), who developed the Rotterdam model, which could be used to test the theory. In the 1970s and 1980s, more emphasis was placed on flexible functional forms, developed from utility or cost functions. The translog model was developed by Christensen et al. (1975) and the almost ideal demand (AID) system was developed by Deaton and Muellbauer (1980b). During the 1980s and 1990s, these models, with extensions, were used to estimate demand for food products, and more complex flexible forms were also developed.

However, the emphasis was still on the price and income effects, and the approach was frequently the modeling of the representative consumer using time-series data.

The government may influence demand for food products in several ways. One obvious way is through price interventions. The government may use different types of tax, subsidy, and price regulation to influence the demand. To find the effects of price interventions, the demand must be estimated. There is a large body of research in which price elasticities for food products have been estimated. Since the food products are aggregated differently in different studies and, furthermore, conditional as well as unconditional elasticities are calculated, comparability is a problem. However, there are elasticities comparable to those calculated in this thesis. Edgerton et al. (1996) estimated Norwegian own-price elasticities of –0.59 for beef, –0.25 for milk, –0.69 for soft drinks, and –0.55 for vegetables, fruits, and berries. Rickertsen (1998) estimated Norwegian own-price elasticities of –0.72 for meats, –0.27 for milk and cream, –0.71 for soft drinks, and –0.60 for fresh vegetables.

Other obvious ways the government may influence demand is through income taxes or direct money transfers to target specific households. Income (or total expenditure) elasticities for food products are typically less than one, meaning that these products are normal goods. Then, when income increases, demand for these products will increase but the income share will decrease. The estimated Norwegian total expenditure elasticities in Edgerton et al (1996) are 0.83 for beef, 0.59 for milk, 1.18 for soft drinks and 0.29 for potatoes and fresh vegetables. This classifies soft drinks as luxury goods.

During the 1980s and 1990s, there was further research on the inclusion of explanatory variables other than prices and income. In particular, how information from advertising, health and nutrition, and food scares affects consumption of various food products has occupied researchers of food demand. Information is difficult to measure and proxy variables are used. Advertising is typically measured as total spending on advertising in different time periods, and health information is often measured as the number of articles in scientific medical journals that link food ingredients such as fat and cholesterol with heart diseases. The latter approach was first used by Brown and Schrader (1990). They noted that per capita consumption of eggs in the USA declined steadily from 1955 to 1987. This happened despite a large downward trend in real prices of eggs and a huge increase in real income. The hypothesis underlying their cholesterol index is that consumers' attitude towards cholesterol change slowly as scientific information is accumulated. Consumers receive health information from different sources, including newspapers, television, friends, etc., so that the number of articles in scientific journals is just a simplification of the diffusion of health information. The Brown and Schrader index has been updated, modified, and used in several studies. Chern et al. (1995) included one version of the index in a Bayesian model to study the demand for fats and oils in the USA, and Kinnucan et al. (1997) included the index in a demand system to study the demand for meat and fish in the USA. Rickertsen et al. (2003) included an extended and modified version of the index to study the demand for meat and fish in the Nordic countries. Health information may also be measured in other ways. Because there is a strong positive relationship between education and nutrition intake, Variyam (2003) included education level as a proxy for information in a household production model. Wang et al. (1996) and Yen et al. (1996) used dummy variables that stated how much the people in question knew about health and diets.

Food scares may be measured in the same way as health information; i.e., as the number of articles or as dummy variables. Smith et al. (1988), studying the loss of sales because of contaminated milk in Hawaii, included in their model an index based on the number of articles in local newspapers. They coded the index according to the positive or negative information content of the articles. Burton and Young (1996) and Burton, Young, and Cromb (1999) constructed an index from newspaper articles about the BSE scandal in the UK.

The advertising effects are typically much smaller than the price effects. Brester and Schrader (1995) estimated the own-advertising elasticities for beef in the USA to be 0.006, whereas Piggott et al. (1996), using an alternative model specification, estimated the elasticity to be between 0.02 and 0.04. The second essay in this thesis lists a few studies estimating the effects of advertising for milk. The effects vary from 0.00 to 0.09. Rickertsen et al. (1995) estimated the demand for vegetables in Norway and found no significant effects of advertising.

Effects from health information vary considerably between countries and between methods. In a European study, reported in Chern and Rickertsen (2003), an extended version of the Brown and Schrader index was used in different studies. Although the health-information elasticities in the French study (Nichèle, 2003) varied from –0.30 for beef to 1.03 for milk, Rickertsen and von Cramon-Taubadel (2003) found very small and mostly nonsignificant health elasticities for meat products and fish in five other European countries. Rickertsen and Kristofersson (2003) showed that the health effects may vary because of autocorrelation in the models.

The effect of food scares on the demand for food products will naturally vary according to the nature of the food scare and the probability of purchasing contaminated food. Usually, short-run and long-run effects are different. Although the consumption of red meat in the UK fell by 40% immediately after information about the connection between BSE and Creutzfeldt–Jacob disease was released (Lloyd et al., 2003), consumption recovered afterwards. Burton et al. (1999) estimated the long-run loss of market share for beef to be 4.9 percent of the total meat consumption.

Kinnucan et al. (2003) discuss positive and negative information. They claim that negative information is more effective than positive information. Reasons for this may be that negative information tends to be regarded as more credible than positive information from advertising, which is common. Negative information of health aspects typically comes from health authorities whereas positive information is industry based.

Nonstationarity of time-series data is a serious problem that has also been investigated in demand studies during the last decade. When some of the data series in a model are nonstationary, conventional *t* and *F*-tests, among others, are not valid and the models based on these data may give spurious results. When all data series are stationary, however, estimation by conventional techniques may be done and the tests may be employed as normal. When all data series are nonstationary but integrated at the same order, the demand equations represent a long-run relationship between the variables only if the variables are cointegrated. The work of Davidson et al. (1978) to model aggregate consumption in the UK by an error-correction model had important influence on the development of cointegration analysis. Engel and Granger (1987) showed the connection between error-correction models and cointegration, and they proposed ways to test for long-run relationships. Since then, their methods have been used to estimate single- equation models in many areas. In consumption studies, Johnson et al. (1992) estimated the demand for alcohol in Canada by using the Engel and Granger two-step method, and Song et al. (1997) used it as one of many different methods for modeling the demand for food in the USA and the Netherlands. Later, other methods to estimate and test for cointegration were developed. However, only in the second half of the 1990s were satisfactory methods for estimating cointegration in demand systems developed. Attfield (1997) specified a demand system in triangular form and applied maximum likelihood techniques to estimate the model of six commodity groups. Pesaran and Shin (2002) used Vector Autoregression (VAR) with the Johansen (1988) cointegration procedure as a framework for estimating a demand system. The Pesaran and Shin framework was used in Kaabia et al. (2001) to study the effects of health information on the demand for meat in Spain.

The Essays

Essay 1: The BSE Crisis and the Reaction of Norwegian Consumers

The main objective of the first essay is to estimate the effects of information about the BSE scandal on the Norwegian beef consumption. The Norwegian beef industry has not been exposed to BSE and, because of restrictions on imports, the risk of eating BSE-contaminated meat is relatively low in Norway. However, the media focus on the issue and the increased beef import might have affected the beef consumption. An error-correction model is used to predict the demand for beef. The predictions for 1996, the year when the link between BSE and the human version, Creutzfeldt–Jacob disease, was detected, were estimated. A Chow-predictive test and a dummy variable test did not indicate that the BSE crisis affected beef consumption in Norway. It is argued that the consumers have confidence in the Norwegian beef for three reasons. First, no cases of BSE have been detected in Norway. Second, Norway did not import beef from countries with BSE-infected herds. Third, the consumers seem to trust agricultural producers and the public authorities.

The main contribution of this essay is the empirical result that no change in the Norwegian beef demand pattern was caused by the BSE scandal.

Essay 2: Fluid Milk Consumption and Demand Response to Advertising for Non-Alcoholic Beverages

Norwegian milk consumption has declined steadily over the last 20 years, despite the dairy industry's spending increasing amounts on advertising. The profitability of advertising is of importance for producers. Does increased expenditure on advertising result in increased sales and profits? We estimated a demand system of beverage products with advertising expenditures included as independent variables using time series data. We used the model to analyze the profitability of advertising for the milk producers. Our results suggest that generic milk advertising is not profitable for the producers.

The main contributions of this essay are as follows. First, a demand system framework is utilized to take substitution effects of advertising into account. Second, fluid milk is divided into whole and low-fat milk to study possible differences in advertising responses. Third, the effects of generic advertising are positive and significant for whole milk and negative and significant for low-fat milk. Finally, our empirical results show that milk advertising does not increase producer net revenues.

Essay 3: Forecasting Ability of Theory-Constrained Two-Stage Demand Systems

Making demand forecasts for food products with a reasonable degree of accuracy will always be a great challenge for producers' organizations, regulating authorities, and the government. In this article, we use time-series data and apply system estimation of a two-stage demand system for eight beverage and cheese products. Furthermore, we compare eight different ways of making demand forecasts conditional on changes in prices and income. A two-stage system implies interconnections between the stages. These interconnections can be modeled to make unconditional forecasts, or the second stage can be modeled separately to make conditional forecasts.

The results from Kastens and Brester (1996) suggest that making one-period ahead forecasts using elasticities gives better results than the statistical models. Moreover, the imposition of demand restrictions improves the forecasts, even though they are rejected by statistical tests. In this essay, we try to extend these results to a two-stage model and nine forecasting periods. For our data, conditional forecasts are superior to unconditional forecasts, and forecasts derived from elasticities are superior to direct statistical forecasts.

Imposition of homogeneity and symmetry restriction of consumer theory do not improve the forecasts.

The main contribution of this essay is to extend elasticity-based forecasting to two-stage demand systems. Comparing forecasts from conditional and unconditional models has, to our knowledge, not been done before. For our data, the conditional forecasts are superior to the unconditional forecasts. In line with Kastens and Brester, we find that the forecasts obtained by using elasticities are more accurate than those from pure statistical models. Contrary to Kastens and Brester, the imposition of the demand restrictions does not improve the forecasts.

Essay 4: Public Policies and the Demand for Carbonated Soft Drinks: A Censored Quantile Regression Approach

The main objective in this essay is to find out if households consuming large amounts of carbonated soft drinks containing sugar respond differently to price changes than do medium- and low-consuming households. Heavy consumption of soft drinks may contribute to obesity, stroke, and cardiac problems, whereas low and moderate consumption does little harm. Censored quantile regression techniques are used to estimate the demand model and it is compared to the symmetrically censored least-square model of Powell (1986b) and the Tobit model of Tobin (1958).

The results show that heavy drinkers are more price and expenditure responsive than are light drinkers. Further, age has a negative effect upon consumption in all quantiles. Temperature has a positive, albeit similar, effect on consumption in the whole distribution. The change in bottle type from a 0.33 liter glass bottle with an iron cap to a 0.5 liter plastic bottle with a screw cap in 1991, caused the demand to shift upwards by about 10 percent in all quantiles.

The study shows that increasing taxes on carbonated soft drinks containing sugar will lead to a small reduction in consumption by small and moderate consumers and a huge reduction in consumption by heavy consumers.

The main contribution of this essay is the identification of different elasticities for sugary carbonated soft drinks in different parts of the conditional distribution. In addition, the censored quantile regression model has, to my knowledge, never been used to estimate the effects of changing prices on the demand for a food product. Finally, the effects of a change in the VAT on sugary soda demand are of importance for public health authorities.

Essay 5: A Censored Quantile Regression Analysis of Vegetable Demand: Effects of Changes in Prices, Income and Information

Many diseases, including cardiovascular diseases, certain types of cancer, obesity, and diabetes, are linked to dietary behavior and the associated costs are high. A low intake of fruits and vegetables is among the six leading diet-related risk factors according to the World Health Organization (2002). In this essay, we focus on the low vegetable consumption in Norway, and what the authorities may do to increase the demand. We use censored quantile regressions and quantile regressions to investigate the behavior in low- and high-consuming households. Furthermore, we discuss how the authorities may increase vegetable consumption. Removal of the value-added tax for vegetables, income increases, and health information are unlikely to substantially increase purchases in low-consuming households. Nevertheless, information provision is cheap and best targeted at low-consuming households. The results of the censored quantile regression and the Tobit model are very similar at the mean. However, the Tobit model does not take into account the different behavior of households consuming large and small quantities of vegetables.

The main contribution of this essay is the identification of differences in behavior regarding vegetable consumption in the low- and high-consuming households. In addition, the results suggest that increased health information may be more efficient at increasing consumption in low-consuming households, which is an important finding for public health authorities. Finally, and as discussed above, censored quantile regressions have rarely been used in food-demand analysis.

Some Similarities and Differences between the Essays

The static neoclassical demand theory for nondurable consumer goods is a well-documented part of economics. The essays are built upon this theory as described in, for example, Deaton and Muellbauer (1980a). Empirical results that may be taken as rejections of this theory are frequently reported; however, I believe that these rejections have more to do with the data and the way the tests are performed than the theory itself. Hence, in the five essays, the theory is imposed as far as possible. Homogeneity is always imposed and symmetry is imposed in essays 2 and 3 where systems of demand equations are estimated.

In three essays, single-equations are estimated for different reasons. In the first essay, a single-equation framework is selected to investigate the time-series properties of the data. At the time of writing the paper, the theory for investigating these properties within a complete demand system was not fully developed. Quantile regressions cannot incorporate across-equation restrictions, and they cannot be estimated as a complete system of demand equations. Consequently, a single-equation framework is also used in the two essays using quantile regressions. In essays 2 and 3, two-stage demand systems are estimated; however, only in essay 3 are the two stages explicitly linked together, because both stages are used to construct the forecasting model. In essay 2, the focus is on advertising. Because advertising does not contribute to the explanation of the demand for nonalcoholic beverages at stage 1, conditional and unconditional advertising elasticities are similar for all beverages products analyzed.

Two functional forms are used. The homogeneity-restricted double-log model is used in essay 1, the first stage of the model in essay 2, and in the models in essays 4 and 5. This model was the basis of most of the famous analysis of Stone (1954a). The model is described in Deaton and Muellbauer (1980a: 60–64). The almost-ideal-demand (AID) system of Deaton and Muellbauer (1980b) is used in the second stage of the model in essay 2 and in both stages of the model in essay 3.

In this thesis, either time-series or cross-sectional data are used. Time-series data are well suited for making forecasts for the representative consumer or for the total sale of a product. Moreover, this type of data is well suited to finding the effects of factors that change over time, such as prices and advertising, and other types of information. The dynamics in the adjustment process, when prices or income change, may also be explicitly modeled. However, there are some disadvantages with using time-series data. First, demand responses of different household types cannot be analyzed. Second, the observations are often not independent across time and they are frequently trended. Methods to handle autocorrelation and nonstationary data may, therefore, be required. In a pure cross section, there is no time variation, and so we measure variation across the households. Cross-sectional data are well suited to estimating income (Engel) elasticities, effects on consumption of age, places of residence, and different household types. However, using household data also creates a zero-observation problem. Not everybody eats meat, drinks milk, or eats vegetables. The challenge is to handle these zero observations. The household may be recorded with zero purchase of a product for several reasons. First, the household may not like the product, which means that, even if income, prices, or other external factors change, the household will still not buy the product. Another reason for zero purchase may be an economic reason.

Potential buyers may not purchase a product if the price is too high or their income is too low. This means that, if their income increases or the price decreases, they will consider buying the product. Finally, they might be recorded with zero purchase because the observation period is too short relative to the frequency with which they buy the product. In the case of a price decrease or an income increase, they might consider increasing the purchase frequency. In this thesis, when zero expenditure is present, we use censored quantile regression techniques and, hence, do not need to assume anything about the problem.

In the three essays using aggregate time-series data, we have modeled the representative consumer. In the first essay, a single-equation forecast model is used in various ways to find out if the BSE information had any effects on the demand for beef in Norway. The idea behind the forecast model is a simple cointegration analysis where the two-step Engle and Granger (1987) methodology is used. First, a long-run cointegration equation is estimated, the residuals are tested for stationarity, and, if this is not rejected, the lagged residuals from this equation are inserted into a short-term model as an error correction term. In the second and third essays, we estimate systems of demand functions using time-series data. We assume weak separability and two-stage budgeting. Weak separability of preferences means that commodities can be partitioned into groups so that preferences within one group can be described independently of the quantities in other groups. The idea of two-stage budgeting suggests that the consumers can allocate total expenditure in two stages: at the first stage, expenditure is allocated to broad groups of goods, and at the second stage, group expenditure is allocated to individual commodities. Two-stage budgeting implies that changes in prices, total expenditure, advertising, trends, and season in one subsystem affect other subsystems through the total expenditure term. We take care of all the systems and interconnections between them when calculating unconditional elasticities.

Essays 1, 2, and 3 use four-monthly time-series data for beef, dairy products, and beverages. We used four-monthly instead of quarterly data because the Forecast Committee for agricultural products held their meetings every fourth month and they want to base their forecasts on four-monthly data. The use of four-monthly data has some advantages. The Easter holidays, when demand for pork, steak and eggs is high, will always be included in the first four-month period. The summer season, which is barbecue season, is not divided as in the quarterly data. Finally, the demand for lamb and sheep, which is highest in the fall when fresh meat is available, is always in the third four-month period.

In essays 4 and 5, cross-sectional data from Statistic Norway's yearly consumer surveys were used. In essay 4, data from 1989 to 1999 were used. In Essay 5, data from 1986 to 1997 were used to estimate vegetable demand. We did not include the data for 1998 and 1999 because the health-information data were only available up to 1997. We studied the role of prices, income, and sociodemographic factors such as age, family type, and place of living on household demand. Quantile and censored quantile regressions were used. The quantile regression model introduced by Koenker and Bassett (1978) fits quantiles to a linear function of covariates. The model may be specified as a minimization problem and solved by linear programming techniques. A few statistical program packages such as Stata (StataCorp, 2003) have implemented algorithms to solve these minimization problems. Powell (1984, 1986a) introduced the censored quantile regression model and showed that, under some weak regularity conditions, the estimated coefficients are consistent and asymptotically normal. Buchinsky (1994) suggested an algorithm for estimating the censored quantile model, and his method was used. The quantile models have several advantages over the competing limited dependent variable models, which are described in Amemiya (1984). These models are, in most cases, used to model censored regressions. However, these models require strong distributional restrictions. If the errors are not normally and identically distributed, the coefficients will be inconsistently estimated in limited-dependent-variable models. Quantile regressions do not require these restrictions. Another advantage is that we may model the whole conditional distribution.

Contributions of the Thesis

This thesis has methodological as well as empirical contributions. The methodological contributions are in essays 3, 4, and 5. In essay 3, we compared forecasts from conditional and unconditional two-stage demand models. The results show that forecasting with elasticities from conditional models gives better results than those with unconditional elasticities, which implies that there may be enough to estimate one weakly separable subsystem.

A second methodological contribution is the use of censored quantile regression to estimate censored-demand functions. In particular, when the focus is on the health aspect of demand, the differences between low-, moderate-, and high-consuming households are of vital importance. For example, the primary objective of public health authorities should be to influence people who consume little or no healthy food to consume more, and the consumption by people who consume large quantities of healthy food is of little interest. In the case of unhealthy food, reducing the consumption by high-consuming people may give health benefits, whereas reducing the consumption by people who consume little is of limited interest.

There are many empirical findings in the thesis. In the first essay, it was shown that the BSE crisis did not have any effect on the Norwegian beef consumption pattern. The main reasons are that there have been no BSE cases in Norway and the consumers seem to trust the producers and controlling authorities.

In the second essay, advertising was found to affect milk consumption, but the effect was so small that it was not profitable for the dairy industry to advertise. Further, advertising may have delayed the transition from whole to low-fat milk. The price and expenditure elasticities in essays 2 and 3 are not perfectly comparable because of differences in commodity groupings and sample periods; however, a few comparisons can be made. In essay 2, the expenditure elasticities show that whole milk is an inferior good but low-fat milk is not. In essay 3, the commodity fluid milk was shown to be an inferior good, and the inferiority increased when the expenditure elasticity for milk was evaluated at last values of exogenous variables.

In the fourth essay, the demand for sugary soda was explored. The results show that heavy soda consumers are more expenditure responsive than are moderate or low consumers. Age has a negative effect upon consumption in all the quantiles. The results indicate that a doubling of the production tax and the VAT will reduce consumption by 2 liters per year for moderate consumers and by 74 liters per year for the 5 percent of consumers with the highest consumption. Consequently, these taxes are well suited to reduce soda consumption of the heavy consumers. The own-price elasticity of symmetrically censored least-squares model was calculated to be –0.88 and, at the median, the quantile elasticity was –0.77. This corresponds well to the unconditional own-price elasticity for carbonated soft drinks in essay 3, which was calculated to be –0.90.

In the fifth essay, demand for vegetables was analyzed. The results show that, although prices may have an effect on demand for vegetables in the high-consuming households, they have little influence on the people who consume few vegetables. Health information is cheaper and may be a more cost-effective way of increasing vegetable demand in the low-consuming households.

There are some weaknesses in the thesis as well. In the first essay, the error-correction term in the forecast model had too large an influence in the forecasts. After a few years, the error-correction term had to be deleted when the model was used for operative forecasts. However, even though the model may give erroneous forecasts, the conclusion of the essay stays intact; that is, the BSE crisis in Europe had no consequences for Norwegian beef demand. In the second essay, the advertising expenditure was divided in three to obtain four-monthly data. This procedure was necessary because of the nature of the advertising data, but it may have influenced the results. In the fourth and the fifth essays, even though tests did not reject the null hypotheses of no differences between the price elasticities in the different parts of the conditional distributions, the price elasticities were used for policy scenarios. This was done for three reasons. First, for soda as well as for vegetables, the own-price elasticity in the upper part of the distribution is significantly different from zero at the 5% level, whereas the elasticity in the lower parts is not. Second, the quasi *t*-tests do not take the covariance between the elasticities into account and, hence, they are not very accurate. Third, to evaluate the effects of taxes at different levels of consumption, it is better to use elasticities calculated at that level than to use other values.

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Essay 1

The BSE crisis and the reaction of Norwegian consumers

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L'effet de l'ESB sur la demande de viande bovine en Norvège

Résumé — L'éventuelle existence d'une relation entre la maladie de la vache folle et la maladie de Creutzfeldt-Jakob a sérieusement entamé la confiance du consommateur quant à la garantie sanitaire de la viande bovine dans la plupart des pays européens en 1996.
L'industrie norvégienne de la viande bovine n'a pas été exposée à l'ESB et, compte tenu des importations limitées, le risque de contamination y est relativement faible.
Cependant, en raison d'une demande croissante de viande bovine, des prix à la baisse et d'une production constante, les importations ont eu tendance à augmenter au cours des dernières années. Ce changement, conjugué aux informations diffusées par les médias à propos de l'ESB, pourrait affecter la consommation norvégienne de viande de bœuf.
Trois façons d'examiner si l'information médiatique concernant l'ESB en 1996 a eu un effet sur la demande de viande bovine en Norvège sont ici présentées. Un modèle à correction d'erreur pour la demande de viande de boeuf est estimé à partir de données quadrimestrielles, de 1984 à 1995. Il est utilisé pour prévoir la demande de viande bovine pour chacune des 3 périodes de 4 mois de 1996. Les écarts constatés entre les prévisions et les ventes enregistrées au cours de chaque période se situent dans l'intervalle attendu.
Le modèle est ensuite réestimé sur toute la période, 1996 inclus.
Un test prédictif de Chow est utilisé pour tester l'hypothèse de stabilité du modèle lorsque les nouvelles observations sont prises en compte : celle-ci n'est pas rejetée. Enfin, une variable muette est incluse dans le modèle pour tester la présence de changements dans l'élasticité-prix directe et l'élasticité-dépense. Là-encore, le test de stabilité n'est pas rejeté. Ainsi, ni le modèle de prédiction, ni le test de Chow, ni le test basé sur la variable muette n'indiquent que les informations diffusées par les médias concernant la relation ESB/maladie de Creutzfeld-Jacob aient suscité une perte de confiance chez le consommateur en 1996.

Mots-clés :
viande bovine, ESB, économétrie, Norvège

The BSE crisis and the reaction of Norwegian consumers

Summary — *A forecast model examined the influence of the BSE crisis in 1996 on Norwegian consumers' beef demand pattern. The Norwegian beef industry has not been exposed to the BSE and due to restricted imports the risk of eating BSE contaminated meat is relatively small in Norway. However, due to increased demand for beef together with lower prices and constant production the beef imports have increased in recent years. Together with information in the media about BSE this change might have affected the Norwegian beef consumption. An error correction model is used to predict the demand for beef. The predictions for 1996 together with a Chow predictive test and a dummy variable test do not indicate that the BSE crises affected beef consumption in Norway. Changes in real prices of beef and other meats and in consumption expenditure were found to explain changes in beef consumption.*

Key-words:
beef demand, BSE, econometrics, Norway

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CONCERN over a possible link between the mad cow disease and Creutzfeldt-Jakob disease led to a significant loss in consumer confidence in the safety of beef throughout much of Europe in 1996. The Norwegian beef industry has not been exposed to the BSE syndrome, and due to the restricted import the risk of eating BSE contaminated meat is relatively small in Norway. (However, due to increased demand for beef together with lower prices, increased income among the consumers and nearly constant production, the import has increased.)

When the BSE crises in the UK became a media event in Norway in March 1996, the Norwegian government and the Norwegian meat Co-operative quickly informed consumers that Norway did not import beef from the UK or other countries in which the beef might be contaminated by BSE. Beef has not been imported from the UK since about 1980. In 1992 when the only importer of meat was the meat Co-operative, they made a decision not to import beef from the UK because of the problem with the BSE. The Co-operative feared the consumers' reactions if they should sell contaminated meat. Even if the illness was at that time not thought to affect human beings, the sale of British meat in Norway could affect the confidence in Norwegian beef. In the supermarkets and the restaurants you can not tell the origin of the meat. Before 1995 the main import of beef came from the other Scandinavian countries. In 1995 the import regime was changed due to the WTO agreement. After this year Botswana was the biggest exporter of beef to Norway. The total import of beef was about 1000 tons per year in the years from 1987 to 1994. In 1995 the import increased to about 3000 tons and in 1996 it was 5000 tons.

Together with the information in the media about BSE this change might have affected the Norwegian meat consumption. Nearly every day in the beginning of 1996 the newspapers and the television showed photos of contaminated animals in the UK and this may have impacted upon the consumers. In spite of the insistence of the Norwegian industry that the beef in Norway was safe, consumers might have been afraid that the meat might have been imported from a high risk area or smuggled into the country.

The effects of the BSE crises on beef consumption patterns have not been widely analysed in the litterature. Burton and Young (1996 and 1997) estimated systems of meat demand equations. To measure the impact of the media coverage of BSE on meat demand in UK they incorporated a media index based on the number of UK newspaper articles which referred to BSE. Their conclusion is that the media information of BSE reduced the budget share of beef both in the short and the long run. Latouche *et al.*, (1998) conducted a survey in Rennes (France) to analyse consumer behaviour towards meat after the BSE crises: Measuring the willingness to pay they concluded that there is a growing demand for safe products. Hadjikani and Seyed-Mohammad (1997) conducted surveys to show how the media coverage of the BSE crises affected Swedish consumers. They made one survey in May 1996 and another in August-September 1996, when the intensity and magnitude of the media coverage were less. Their results indicate more mistrust towards meat with origin close to England. The mistrust was against other English products as well as meat. When the media coverage dropped, the mistrust against English products dropped too. A Swiss study (Morabia *et al.*, 1999) concluded that the Geneva women changed their dietary habits from beef towards chicken in 1996.

In this paper three methods of capturing the effects of BSE on the aggregate demand for beef in Norway are used. A forecast model which is estimated with data from 1984 to 1995 is used to make forecasts for beef sale in 1996. The forecasts are discussed and the results are compared with the recorded sale in that period. The second method is using a Chow predictive test to test if inclusion of the data for 1996 in the model make the parameters unstable. The third method consists in including a dummy variable to check if the own price elasticity, the expenditure elasticity and a trend term has changed in 1996. Neither of the tests indicates that the information concerning the BSE in the media in 1996 had any effect on the Norwegian beef demand pattern.

The paper proceeds as follows. First the data is described and the error correction model used for forecasting the beef demand is presented. Then the model is utilised for demand forecasts for beef and these results are discussed. After that, the Chow test and the dummy variable tests are performed and discussed. Finally, the reasons why the Norwegian consumers' beef consumption was not affected by the BSE scandal are discussed.

Model and data

A prediction model has been used to examine the influence of the BSE crisis in 1996 on Norwegian consumers demand pattern. An error correction framework is used to construct a simple demand model for beef which takes account of seasonal variations. Four-monthly wholesale data for the period 1984 to 1995 was used in the estimation of the prediction model. The forecast model is estimated on the basis of four-month periods (instead of quarterly periods which is more common) to capture the structure of the Norwegian meat demand. Easter, when the demand for pork shifts upwards due to eating traditions, is always in the first four-month period, and summer, which is barbecue season, is treated in the second four-month period. The prices and the households' consumption expenditure are shown in figure 1. The development of the sales of beef, pork and lamb are shown in figure 2.

The meat prices (deflated with the consumer price index) were relatively stable from 1984 to 1992. After that they started to decline. The price of beef was 15.2 percent lower in 1995 than in 1992. The price of pork was 22.9 percent lower and the price of lamb was down 13.3 percent. The downward trend in the meat prices from 1992 was politically decided. In Norway the maximum wholesale prices are decided in yearly negotiations between the farmers organisations and the government. To prepare for increasing international competition for foodstuff and a possibly new GATT/WTO agreement the government decided in 1991 that the Norwegian food prices had to be reduced.

Recession hit Norway in 1986 and private real expenditure of the households started to fall in that year. It did not catch up to pre-recession level until 1993. The sale of beef started to rise in 1993 due to the lower prices and increased income among the consumers. The sale of beef was 11.5 percent higher in 1995 than in 1992.

Figure 1.
Real prices of beef, pork, and lamb, and the households' consumption expenditure (1984.1=1)

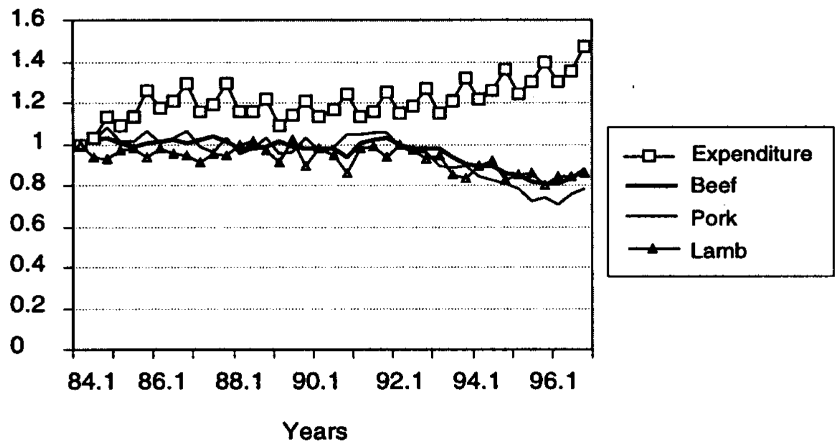
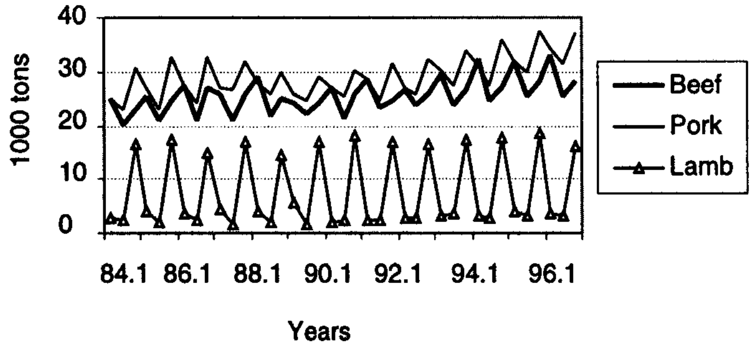


Figure 2.
Sales of beef, pork, and lamb



Error correction models are widely used in applied econometrics. The work of Davidson *et al.* (1978) to model aggregate consumption in the UK has had important influence on time series econometrics. To take account of seasonality they used seasonally differenced variables and they included an error correction mechanism in their model to correct for the deviation from the long run equilibrium. Their work contributed to development of cointegration analysis and the relation between cointegration and error correction models. These models are extensively described in Banerjee *et al.* (1993). The use of seasonal integration and tests for seasonal cointegration are described in Charemza and Deadman (1992).

The following error correction model is utilised to forecast the future beef demand in Norway (with t-values below the parameters):

$$\widehat{\Delta_3 x_{1t}} = \underset{(-2{,}86)}{-0{,}74}\,\Delta_3 p_{1t} + \underset{(0{,}94)}{0{,}17}\,\Delta_3 p_{2t} + \underset{(0{,}65)}{0{,}17}\,\Delta_3 p_{3t}\cdot D_{3t}$$

$$+ \underset{(3{,}30)}{0{,}62}\,\Delta_3 \exp_t - \underset{(-4{,}45)}{0{,}81}\big[x_{1,t-3} - 7{,}95 - 0{,}16\, D_{1,t-3}$$

$$+ 0{,}08\, D_{2,t-3} + 0{,}39\, p_{1,t-3} - 0{,}76 \exp_{t-3}\big]$$

where:

Δ_3 = the third difference operator (the difference of the variable between this period and the same period one year ago),

x_{1t} is the natural logarithm of the sale of beef (in tons) in period t,

p_{1t}, p_{2t}, p_{3t} are the natural logarithms of the prices of beef, pork and lamb respectively in period t,

exp_t is the natural logarithm of the total private expenditure of the Norwegian households,

and D_1, D_2 and D_3 are dummy variables for the three four-month periods. The prices and the total expenditure are deflated by the consumer price index. The seasonal dummy D_{3t} appears with the price of lamb because lamb is mainly consumed in the slaughtering season which takes place in the autumn. In the first and the second season there is not fresh lamb available.

The equation was estimated by the Engle-Granger (1987) two-step procedure: First the static long run equation (in brackets) was estimated using the method of ordinary least squares (OLS). Dickey-Fuller tests on the residuals rejected the null hypotheses of unit roots, hence they indicated that the variables were cointegrated in season. The residuals were lagged three periods and put into the model. This equation was then estimated by OLS. The purpose of modelling the first static equation with fewer explanatory variables than the equation was to estimate on only stationary variables. Dickey-Fuller tests performed on the residuals of the long run equation rejected the null hypotheses of stationarity when the prices of lamb and pork were included. Table 1 shows the statistics from the estimation.

Table 1. Test statistics for the error correction model for beef demand

%MAE	R^2_{adj}	DW	Q	Q*	λ
3.2	0.56	1.94	12.02	16.97	4.79

Critical values (5 % significance level):
DW: $d_L = 1.16$, $d_U = 1.80$ Q, Q^*: $\chi^2\ (15) = 25.0$ λ: $\chi^2\ (5) = 11.07$

The percentage mean absolute error (*%MAE*) is the mean difference (in percent) between the actual and the predicted value of the sale in a static simulation (one-period forecasts) on the data from 1984 to 1995. R^2_{adj} is R^2 adjusted for degrees of freedom and *DW* is the Durbin-Watson statistic. The Box-Pierce statistic Q and the Box-Ljung statistic Q^* can be used to test for autocorrelation for a given order. The null hypotheses of no autocorrelation is rejected if $Q, Q^* > \chi^2\ (m)$, where m is the number of lags the residuals are tested for. λ is the test statistic for the Breusch-Pagan test for heteroscedastisity. The null hypotheses about homoscedastic error terms is rejected on a 5 %-level if $\lambda > \chi^2\ (n-1)$. n is the number of parameters in a regression of normalised residuals on possible heteroskedastic terms.

From the error correction model we can see that the own price elasticity, the expenditure elasticity and the error correction term are all significantly different from zero and they all have the expected sign. An own price elasticity of – 0.74 and an expenditure elasticity of 0.62 seem reasonable. The cross-price elasticities between pork and beef and between lamb and beef are not significantly different from zero. But these are kept in the prediction model because we have reasons to suppose that the prices of pork and lamb contribute to explaining changes in the demand for beef.

Table 1 shows that a static simulation on the data from 1984 to 1995 gave a mean difference between the actual and the predicted values of the sale of beef of 3.2 percent. *DW*, Q and Q^* all indicate that autocorrelation is not a problem in the equation for beef. The Breusch-Pagan test did not reject the null hypothesis of homoscedastisity.

The model predictions for 1996

The model has been implemented in the programming language Visual Basic to give predictions for future beef demand in Norway. The users of the program have to give the prices of beef, pork and lamb as input to the model in the prediction period. The model also demands the consumer price index and private consumption for the same period. The maximum prices of beef, pork and lamb in Norway are decided by yearly negotiations between the government and the farmers' organisations. The Norwegian Meat Co-operative which regulates the market for meat has a market share of about 80 percent. According to the market conditions they decide the price levels below the maximum prices. Hence, endogenity of the prices is no problem in the demand model.

Table 2 shows the input data to the model and the results from the model prediction of beef sale in 1996. As input data are used the recorded prices and the total private expenditure in 1996 (both deflated with the consumer price index). The table shows the real prices for the three four-month periods of the year and the growth in the variables from the same period last year. The same is shown for the aggregate private expenditure in 1996. The model forecasts for beef and the recorded beef sale follow. At the bottom of the table the level and the percentage differences between the predicted and recorded sale (error) is reported.

Table 2. **Real prices of beef, pork and lamb, total expenditure, forecasted and recorded beef sale and the difference between the forecasts and recorded sale**

	1. period 1996		2. period 1996		3. period 1996		The year 1996	
	Level	Δ %	Level	Δ %	Level	Δ %	Level	Δ %
Price beef	34.8	-4.0	35.8	2.1	37.5	8.1	36.0	1.7
Price pork	26.7	-8.3	28.3	4.8	29.4	6.3	28.2	0.8
Price lamb	39.9	-0.3	39.6	-1.7	40.6	8.2	40.4	5.5
Expenditure	128.7	4.9	134.2	3.9	145.5	5.2	408.4	4.7
Forecasted beef sale	32.8	3.3	26.3	3.7	29.5	4.5	88.5	3.8
Recorded beef sale	33.2	4.7	25.3	-0.1	28.9	2.6	87.4	2.6
Error	-0.4	-1.3	1.0	3.8	0.5	1.9	1.1	1.2

The prices in level are in NOK/kg, total expenditure of the households are in billions of NOK. The forecasted and recorded sales are in 1000 tons. Δ% is the growth in prices, expenditure and sale from the same period the year before. The error term is the difference between the forecasted and recorded sale (in 1000 tons and %).

The model forecasted that the sale of beef would grow 3.3 percent in the first period of 1996, 3.7 percent in the second period and 4.5 percent in the third period. This would give an increased 3.8 percent in 1996 compared to 1995. The recorded sales grew 4.7 percent in the first period, declined 0.1 in the second period and grew 2.6 percent in the third period. This is a difference between the predicted and recorded sale of – 1.3 percent, 3.8 percent and 1.9 percent. In sum the sale of beef increased by 2.6 percent in 1996. In total for 1996 the error was 1.2 percent. From the table we can see that the real price for beef increased in 1996. This price increase contributed to a negative effect on the sale. The increased prices of pork and lamb (in the third period) gave the opposite effect on beef. The increased total expenditure among the households contributed to a higher level in the beef sale of 1996. In the forecast model the partial effects of the changed value of the variables on the change in the sale of beef is approximately given by:

(% change in sale of beef) =
*(elasticity of variable on sale of beef) * (% change in explaining variable)*

Table 3 gives the approximate partial effects of the prices, consumption and the error correction term on the forecasts of the sale of beef in 1996. From the table we can see that the decline in the price of beef in the first period contributes with 3 percent increased sale in the model prediction. The price of pork has a downward effect of 1.5 percent, private consumption gives an upward shift in the model prediction of 2.9 percent and the error correction term gives the prediction a partial downward shift of 1 percent. The negative error correction contribution in the first period of 1996 is due to the sale in the first period of 1995 which was below the long run path. In the second period the error correction term shifts the prediction 2,0 percent and in the third period the partial effect of the error correction mechanism is 4,9 percent. In the last period this effect contributes to dampen the large negative effect of the own price of beef.

Table 3. **The partial effects on the forecasts of the changes in the prices of beef, pork and lamb and the effects of the households' real expenditure and the error correction mechanism (in %)**

	Price beef	Price pork	Price lamb	Expenditure	Error correction
1. period 1996	3.0	-1.5	0	2.9	-1.0
2. period 1996	-1.5	0.8	0	2.3	2.0
3. period 1996	-5.6	1.1	1.0	3.0	4.9

The difference between the model predictions and the recorded sale is relatively small in the three periods in 1996. The model predicted a higher demand than recorded in the last two periods. This can lead us to believe that all the information about the BSE and the Creutzfeldt-Jakob Disease in the two last periods in 1996 had effect on the consumption of beef after all. But as table 1 shows, the mean percentage error in the estimating period was 3.2 percent. A model predicting a sale of 3.8 and 1.9 percent more than the recorded sale is within the expected range. Part of the over prediction in the last two periods was caused by the error correction term which had a very large effect, especially in the third period.

The tests for BSE

The Chow prediction test can be used to check the stability of the regression coefficients. We want to check if the inclusion of the observations in 1996 bring instability to the model. To perform this test we have to estimate the regression model to the data set 1984 to 1996. Then we estimate the model to the data set 1984 to 1995.

The test statistic

$$F = \frac{(RSS - RSS_1)/n_2}{RSS_1 \;/\; (n_1 - k - 1)}$$

has an F-distribution with d.f. n_2 and n_{1-k-1} where:

n_1 = the number of observations from 1984 to 1995 (= 33 observations),

n_2 = the number of observations in 1996 (= 3 observations),

k = the number of explaining variables,

RSS = the residual sum of squares from the regression based on $n_1 + n_2$ observations,

RSS_1 = the residual sum of squares from the regression based on n_1 observations.

The F-statistic was calculated to $F = 0{,}24$. From the F-tables with d.f. 3 and 27 we find that the 5 % point is approximately 2,95. Thus at the 5 % level of significance, we do not reject the hypothesis of stability.

An F-test with dummy variables was used to check if data indicates any change in the own price and expenditure elasticity of beef in 1996 and if a negative shift in demand for beef happened that year. A dummy variable, *Dum*, which has the value 0 in the period 1984 to 1995 and the value 1 in the three periods in 1996 was introduced[1].

The terms

$\beta_0 \,.\, Dum,$

$\beta_1\, \Delta_3\, p_{1t} \,.\, Dum,$

$\beta_4\, \Delta_3 \exp_t \,.\, Dum$

were added to the error correction model and the model is then:

$$\Delta_3\, x_{1t} = \beta_0 \,.\, Dum + (\alpha_1 + \beta_1 \,.\, Dum)\, \Delta_3\, p_{1t} + \alpha_2\, \Delta_3\, p_{2t} + \alpha_3\, \Delta_3\, p_{3t}$$

$$.\, D_{3t} + (\alpha_4 + \beta_4 \,.\, Dum)\, \Delta_3 \exp_t + \alpha_5 \left[x_{1,t-3} - \varphi_1 - \varphi_2\, D_{1,t-3}\right.$$

$$\left.- \varphi_3\, D_{2,t-3} - \varphi_4\, p_{1,t-3} - \varphi_5 \exp_{t-3}\right] + u_t$$

where the α's are the price elasticities, the expenditure elasticity and the error correction parameter. The φ's are the parameters from the cointegration/long run regression (The cointegration regression, in brackets, is performed on the same observations as the cointegration regression in the forecast model. The long run parameters in the two models therefore have the same values). β_0 is a stochastic trend, β_1 is the change in the price elasticity for beef and β_4 is the change in the expenditure elasticity for beef. u_t is a supposed white noise error term. To test if the own

[1] To capture any possible BSE effect on beef demand it was also tried to set the dummy variable as:

a) 1 in the first and the second period in 1996 and 0 elsewhere

b) 1 in the second and third period in 1996 and 0 elsewhere

The results from the test with these values on the dummy variable did not alter the conclusions from the tests.

price elasticity and the expenditure elasticity for beef have changed in 1996, the new model was first estimated with data from 1984 to 1996 with the restrictions imposed. Then the new model without the restrictions $\beta_0 = \beta_1 = \beta_4 = 0$ imposed is estimated.

An F-statistic may bee used to test simultaneously if the elasticities or the constant term have changed in 1996:

$$F = \frac{(RSS_1 - RSS_2)/k}{RSS_2 \; / \; (n - k - 1)}$$

where:

RSS_1 = the residual sum of squares of the model with restrictions,

RSS_2 = the residual sum of squares of the model without the restrictions,

n is the number of observations from 1984 to 1996 (= 36),

and k is the number of new parameters (= 3).

A t-test showed that none of the dummy parameters were significantly different from zero. The F-statistic was calculated to $F = 0.13$. From the F-tables with d.f. 3 and 32 we find that the 5 % point is approximately 2.90. Thus at the 5 % level of significance, we do not reject the null hypothesis that the parameters have not changed.

Discussion

Why did not the BSE crisis change the beef consumption pattern in Norway when that happened in other European countries? Firstly, there has not been detected any cases of BSE in Norway so the consumer could have confidence in Norwegian beef. Secondly, the Norwegian government and the meat Co-operative quickly informed the consumers that Norway did not import beef from countries with BSE. Thirdly, except from radiation in sheep after the Chernobyl accident in 1986 and scrapie in sheep in 1996[(2)], there have not been major food scares in Norway. The case of scrapie in 1996 may have had some influence on the econometric results, but probably not on the conclusions. In 1996 the sale of lamb dropped 12 percent from 1995 levels, but the sale in 1995 was very high. The prices of lamb increased 7 percent from 1995 to 1996 and that may have contributed to the lower sale as well.

[(2)] In the summer and autumn of 1996 a few cases of scrapie in some Norwegian sheep herds was discovered. The meat Co-operative ensured that they would not sell any sick animals. All infected sheep herds and herds which had been in contact with infected herds were slaughtered. It was stated by experts that scrapie has existed in Europe for 250 years and no link has been established between scrapie and any disease in human beings.

Finally, and perhaps most important, there is the question of trust. The consumer is not able to find out enough about the quality of the meat by looking at it or smelling it. The concept of quality is partly tied to the degree of information about individual products. When such information is lacking, consumer behaviour will be based on trust. In a discussion of food safety, Nygård and Storstad (1998) argue that if the consumers are to buy the food, they have to have trust in the producers, the political authorities and the controlling experts. The producers and the distribution link have to present products that are in keeping with official regulations and that are not dangerous. In addition, the consumer must trust the authorities to have a set of regulations and controls that can provide sufficient safety and security. And there has to exist confidence in the experts' evaluation of risks that are the basis for quality.

According to a survey conducted by a public opinion institute (MMI, 1997), the Norwegian consumers seem to have a very high confidence in the Norwegian food producers. 70 percent of the Norwegian population think that Norwegian agricultural products are of high quality while 27 percent think the products are of average quality. 85 percent think that Norwegian products are safer to eat than imported products. Only 15 percent thought that the origin of food products are not important for their safety.

The trust in the agricultural sector is high because of the small scale production with high degree of public support and very good animal health. A report by the Norwegian Veterinary Association states that the health in Norwegian domestic animals is very good (Skjerve *et al.*, 1996). As an example there were found yearly between 600 and 1 600 cases of salmonella infections during the period 1983-1996. 70 percent of the cases had origin outside the country, 7 percent were from sources inside the country, while the source of origin for the remaining 23 percent were unknown. In Norway it is rare getting sick from eating infected food.

Comparative research concerning trust to the political system and the controlling authorities shows that the Norwegians are more confident to the "system" compared to other countries (Listhaug and Wiberg, 1995). In a comparative study of eight western democracies Listhaug (1998), using data from 1995-1996, found that Norwegians have more trust in the government and national assembly than the other countries in the study (3).

Final remarks

Three ways of examining if the media information about BSE in 1996 had any effect on the beef demand pattern in Norway are presented in this paper. An error correction model for beef demand esti-

(3) The eight countries in this study were Norway, Sweden, Finland, Germany (West), Swizerland, Spain, Australia, and the USA.

mated on four-month data from 1984 to 1995 is presented. The model is then utilised to make forecasts for beef demand in the three four-month periods in 1996. The differences between the forecasts and the recorded sale in these periods are within the expected range. Then the model is re-estimated with the prices, expenditure and beef sale for 1996 included. A Chow predictive test is performed to check if inclusion of the new observations cause any instability to the regression parameters. The null hypothesis of stability in the regression parameters is not rejected. Finally a dummy variable is included in the model to check if the own price elasticity has changed, if the expenditure elasticity has changed or if inclusion of a stochastic trend explains anything new in 1996. The tests performed did not reject the null hypothesis of no change in the elasticities and the trend in 1996. Thus, neither the forecast model nor the Chow test or the dummy test indicate that the information in the media about the connection of BSE with Creutzfeldt-Jakob disease led to a large enough loss of consumer confidence in 1996 to affect aggregate consumption of beef in Norway.

In the final part of the paper the reasons why the Norwegian beef consumption pattern did not change in 1996 are discussed. Firstly, no cases of BSE in Norway have been detected so the consumer could have confidence in Norwegian beef. Secondly, Norway does not import beef from countries with BSE infected herds. Thirdly, except from radiation in sheep after the Chernobyl accident in 1986 and scrapie in sheep in 1996 there have not been any major food scares in Norway. Finally, the Norwegians seem to have trust in the producers, the political authorities and the controlling experts.

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Essay 2

AGRICULTURAL AND FOOD SCIENCE IN FINLAND

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Fluid milk consumption and demand response to advertising for non-alcoholic beverages

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Norwegian fluid milk consumption has declined steadily over the last twenty years, despite the dairy industry spending increasing amounts of money on advertising. Using a two-stage model, we investigate whether advertising has increased the demand for milk. No effect of advertising on the demand for non-alcoholic beverages is found in the first stage. In the second stage, an almost ideal demand system including advertising expenditures on competing beverages is estimated. The effects of generic advertising within the beverage group are positive and significant for whole milk and negative and significant for lower fat milk. The own-advertising elasticity for the combined fluid milk group is 0.0008. This highly inelastic elasticity suggests that increased advertising will not be profitable for the producers. Several cross-advertising effects are statistically significant, emphasizing the usefulness of a demand system approach.

Key words: advertising, almost ideal demand system, milk, Norway

Introduction

Norwegians consume large quantities of fluid milk, however, the consumption has declined steadily over the last twenty years. The per capita consumption decreased by about 20 percent over the 1975 to 1995 period. Moreover, the composition of consumption has changed substantially after the introduction of low fat milk (1.5 percent fat) in 1985. The annual per capita consumption of lower fat (nonfat and low fat) milk has increased from 19 to 100 liters, while the whole milk consumption has dropped from 127 to 33 liters since 1985. The purchasing pattern of other beverages has also changed. The per capita consumption of hot drinks (coffee, tea, and cocoa) declined by more than 20 percent during the period, and the consumption of cold beverages (fruit juices, soft drinks, light beer,

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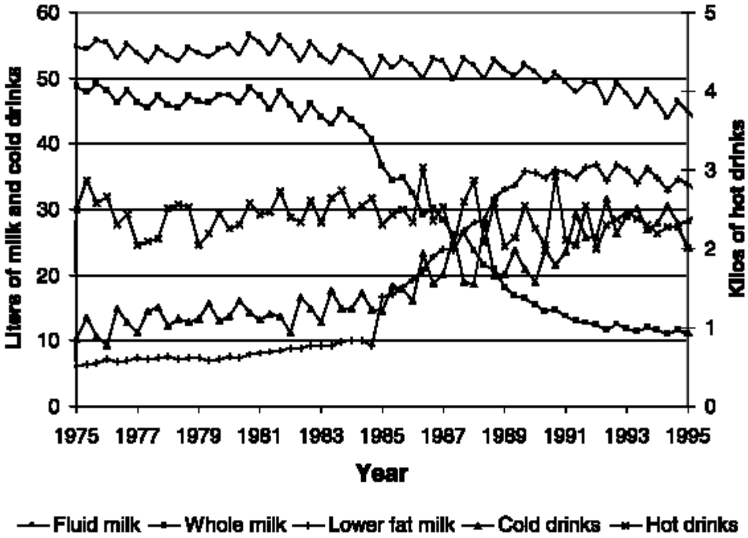

Fig. 1. Per capita consumption of non-alcoholic beverages (Sources: Norwegian Dairy Cooperative and Norwegian Social Science Data Service).

and mineral water) more than doubled. The changes in consumption are shown in Fig. 1. In this figure, and in this study, the prices and quantities are based on four-month intervals. We use a four-month observation period instead of the commonly used three-month observation period (quarterly data) because the Norwegian Dairy Cooperative (Norske Meierier) uses a four-monthly reporting period.

We also observe similar changes in the consumption of beverages in other countries. The US per capita consumption of soft drinks has, for example, increased by 111 percent between 1970 and 1995 while the fluid milk consumption declined by 22 percent (Putnam and Allshouse 1997). The US trend is also toward lower fat milk. The consumption of whole milk was cut by two-thirds between 1970 and 1997 while the use of lower fat milk nearly tripled (Putnam and Allshouse 1998).

The decline in milk consumption causes concern in the dairy industry and it is of considerable interest to investigate to what extent the observed changes can be explained by factors the dairy industry itself can influence, such as changes in advertising. The Norwegian Dairy Cooperative's advertising expenses on fluid milk increased from about NOK 1.3 million in 1975 to about 20 million (approximately US$ 2.2 million) by the end of the period. This is a substantial increase in real terms, since the consumer price index (CPI) quadrupled over the period. However, the expenses are fairly small compared with advertising for cold drinks (NOK 119 million in 1995) and hot drinks (NOK 55 million in 1995). The milk advertising has been directed toward increasing the total sales of fresh milk. The advertising for cold and hot drinks is, by contrast, branded. Brand advertising may both increase aggregate demand for, for example, cold drinks and reallocate market shares among the various brands of cold drinks. This advertising may also reduce the demand for fluid milk over time. Annual current advertising expenditures and the CPI are reported in Fig. 2.

There has been a considerable research activity on the effects of generic advertising on the demand for fluid milk; see, for example, Johnson et al. (1992) and Forker and Ward (1993) for summaries of some results. Recent studies include Suzuki et al. (1994), Reberte et al. (1996), Kaiser (1997), Suzuki and Kaiser (1997), Lenz et al. (1998), Pritchett et al. (1998), Kamp and Kaiser (1999), Tomek and Kaiser (1999), Chung and Kaiser (1999), and Kinnucan (1999). These studies have found a positive, and usual-

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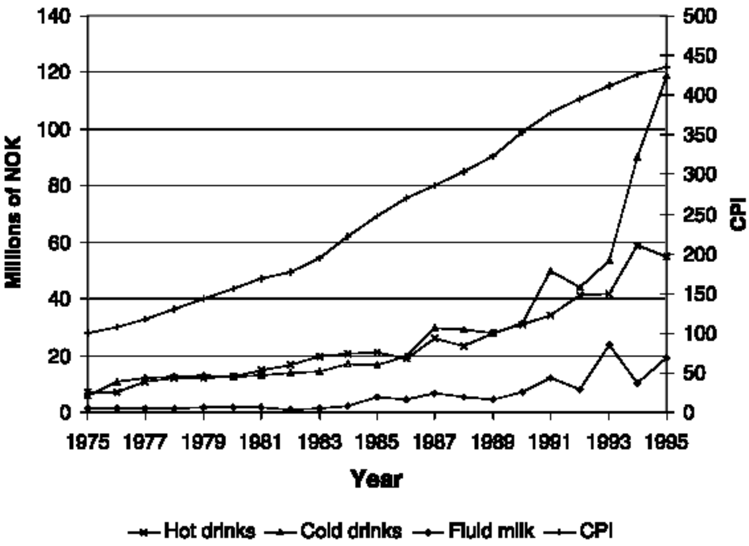

Fig. 2. Advertising expenditures for non-alcoholic beverages and the consumer price index (Sources: ACNielsen and Statistics Norway).

ly significant and substantial, effect of generic advertising for milk on demand for milk. However, the results were obtained using a single-equation framework, which neglects advertising expenditures on substitutes for fluid milk. Goddard et al. (1992) and Kinnucan et al. (2001) used demand systems and found positive but small own-advertising elasticities for fluid milk in Canada and the United States. A demand system allows for cross-commodity advertising effects on competing goods. As advertising expenditures for the various types of non-alcoholic beverages increase, it is not clear to what extent the advertising efforts add to overall non-alcoholic beverage demand or merely cause substitution among beverages. If substitution is important, the effects of milk advertising are better studied in a model incorporating advertising for other close substitutes.

Given consumers' concerns about fat and cholesterol in food and beverages, it is questionable to aggregate the various types of fluid milk. Nevertheless, fluid milk is usually treated as one beverage when the effects of advertising are studied. One exception is Kaiser and Reberte (1996) who concluded that advertising had a positive and equal impact on the demand for whole, low fat, and nonfat milks. We divide fluid milk into two groups, whole and lower fat milk, to detect any differences in sales responsiveness to advertising.

The contributions of this paper are as follows. First, to fix ideas the Norwegian milk market is discussed graphically. Second, a demand system framework is utilized to take substitution effects of advertising into account. Third, fluid milk is divided into whole and lower fat milk to study possible differences in advertising responsiveness. Finally, we discuss whether the advertising causes producer revenue, net of advertising cost, to increase.

Graphical analysis

Even though the government has allowed some competition in the fluid milk market during the last few years, the dairy cooperative was a monopolist during the period of study. Fig. 3 can illustrate this market. We abstract from the marketing channel and the possibility for price-discrimination schemes between fresh and industrially processed milk. Norway is a small-country exporter that can sell excess supply to the world market at the price P_1. At the domestic market the dairy cooperative is a monopolist. Let the domestic demand curve be illustrated by D, the supply curve by S, and the marginal revenue curve by MR. If the cooperative was allowed to determine the domestic consumer price, it would set the price to P_0, the quantity Q_0 would be sold domestically, and the quantity $(Q_1 - Q_0)$ would be exported. However, the government regulates the monopoly by setting the consumer price to P_2. To reduce the production they also use non-tradable and historically based production quotas represented by S^* in the figure. The quota is set larger than the domestic demand at price P_2 resulting in sales of the quantity Q_2 domestically and export of the quantity $(Q_3 - Q_2)$.

Advertising may shift the domestic demand curve. Assuming successful advertising, the demand curve shifts to D^* and exports are eliminated as in the figure. The dairy cooperative is not allowed to increase the price of milk to finance advertising, which has to be financed by transfers within the organization. Advertising has increased the producer surplus with the hatched area *abcd*. If this increase in producer surplus is larger than the direct costs of advertising plus

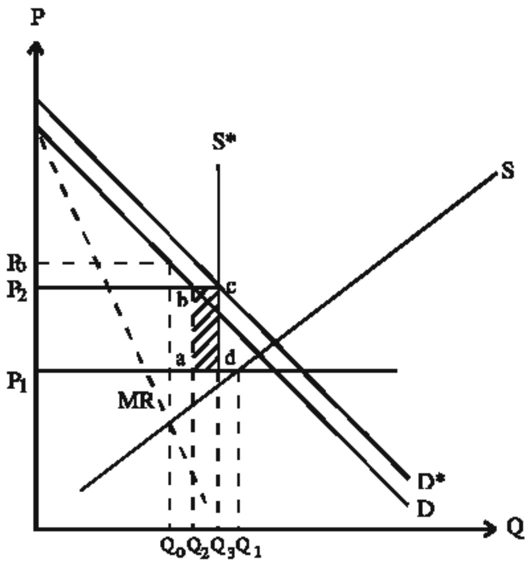

Fig. 3. Advertising in the Norwegian milk market.

the opportunity cost of the capital spent on advertising, the advertising has been profitable for the producers. The change in producer surplus can be calculated as $(P_2 - P_1) \cdot (Q_3 - Q_2)$.

The effects of advertising in the market described above are different than in the markets described in Kinnucan and Myrland (2001). They describe markets where prices are determined under free-market conditions and the law-of-one-price holds. Our market is closer to the supply-managed markets discussed in Kinnucan (1999); however, we have exogenously set prices in combination with a quota that is larger than the domestic demand.

Demand models with advertising effects

We follow Goddard and Amuah (1989), Richards et al. (1997), and Kinnucan et al. (2001) and estimate a two-stage model. In the first stage, the consumer allocates the total expenditure to broad commodity groups, such as non-alcoholic beverages. In the second stage, the total expenditures on non-alcoholic beverages are divided among the individual drinks. Richards et al. (1997) adhered to the theoretical requirements of two-stage budgeting and used the linear expenditure system in the first stage and the almost ideal demand system in the second stage. This approach is, in many ways, desirable and allows the estimation of demand elasticities satisfying the basic properties of demand (homogeneity, symmetry, and adding-up) at both stages. However, we do not use a demand system in stage one because we have no data for the advertising expenditures for goods other than non-alcoholic beverages.

In the first stage, we start with a double-log demand function

$$(1) \quad \ln q_i = \theta_i + E_i \ln x + \sum_{j=1}^{n} e_{ij} \ln p_j ,$$

where q_i is per capita consumption of good i (in our case non-alcoholic beverages), x is per cap-

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ita total expenditure, p_j is the nominal price of good j, E_i is the expenditure elasticity, and e_{ij} is the uncompensated price elasticity for good i with respect to the price of good j. The general relationship between the uncompensated and compensated price elasticities, e_{ij}* is $e_{ij} = e_{ij}* - w_jE_i$, where w_j denotes the expenditure share of good j. Substituting this relationship into equation (1) yields

$$(2) \quad \ln q_i = \theta_i + E_i\left(\ln x - \sum_{j=1}^{n} w_j \ln p_j\right) + \sum_{j=1}^{n} e_{ij}^{*} \ln p_j.$$

The index $\Sigma_j w_j \ln p_j$ is Stone's price index. Moschini (1995) showed that this index is not invariant to changes in the units of measurement. To avoid this potentially serious problem, we use the average expenditure share for each good in the index.

We include an advertising variable, *adv*, to capture the possible effects of advertising expenditure on the demand for non-alcoholic beverages. The current expenditures are deflated with Stone's index, which is a part of the double-log model (2) and closely related to the almost ideal model that is used in the second stage. Seasonality in consumption has proved to be important in numerous studies of consumer demand and it is reasonable to believe that the consumption of beverages is higher during the summer months than in the rest of the year. Consequently, two seasonal dummy variables, D_2 and D_3, which are set to one in the second and third four-month periods, respectively, are included. Other factors of potential importance for demand have also changed. Kinnucan et al. (2001) found that age structure and incidence of dining out had significant effects on milk consumption. Factors such as health information or the introduction of new non-alcoholic beverages may also have affected the consumption. The best way to capture non-economic effects is to include variables closely related to the effects. However, the inclusion of several non-economic variables requires many degrees of freedom and, moreover, we do not have data for these variables. To approximate the total effect of these changes, a trend, t, is introduced and equation (2) is extended to

$$(3) \quad \ln q_i = \theta_i + E_i\left(\ln x - \sum_{j=1}^{n} w_j \ln p_j\right) + \sum_{j=1}^{n} e_{ij}^{*} \ln p_j + a_i\left(\ln adv_i - \sum_{j=1}^{n} w_j \ln p_j\right) + \omega_1 \ln t + \omega_2 D_2 + \omega_3 D_3,$$

where a_i denotes the own-advertising elasticity. Homogeneity of degree zero in prices and total expenditure implies that $\Sigma_j e_{ij}* = 0$ and we impose this restriction.

Deaton and Muellbauer's (1980) almost ideal demand system is used in the second stage. The i-th good's expenditure share is given by

$$(4) \quad w_i = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_j + \beta_i[\ln x - \ln P],$$

where the price index, $\ln P$, is defined by

$$(5) \quad \ln P = \alpha_0 + \sum_{k=1}^{n} \alpha_k \ln p_k + \frac{1}{2}\sum_{k=1}^{n}\sum_{j=1}^{n} \gamma_{jk} \ln p_k \ln p_j,$$

and the other variables are defined as in the first stage.

The price and expenditure elasticities are calculated as

$$(6) \quad e_{ij} = -\delta_{ij} + \frac{\gamma_{ij}}{w_i} - \frac{\beta_i}{w_i}\left(\alpha_j + \sum_{k=1}^{n} \gamma_{kj} \ln p_k\right) \quad \text{and} \quad E_i = 1 + \frac{\beta_i}{w_i},$$

where δ_{ij} is the Kronecker delta ($\delta_{ij} = 1$ for $i = j$, and $\delta_{ij} = 0$ for $i \neq j$). The demand restrictions, $\Sigma_i \alpha_i = 1$, $\Sigma_i \gamma_{ij} = \Sigma_i \beta_i = 0$ (adding up); $\Sigma_j \gamma_{ij} = 0$ (homogeneity); and $\gamma_{ij} = \gamma_{ji}$ (symmetry), are imposed on the system.

As in the first stage, two seasonal dummy variables and a trend variable are included. Furthermore, a dummy variable, *low*, is included to take account of the introduction of low fat milk in 1985. This dummy variable is allowed to interact with the trend, but not with advertising, price, or total expenditure, to save degrees of freedom.

Lee and Brown (1992) claim that, for commodities consumed daily, such as milk, it is difficult to argue that people need more than a few months to purchase the product. Consequently, it is hard to argue for any carryover effect using a longer data interval. In agreement with their point of view, we introduce the vector of current period's advertising expenditures in each demand equation. The advertising expenditures are deflated with the modified Stone index as in the first-stage model. The demand shifters are introduced as modifiers of the intercepts in equations (4), (5), and (6), such that

$$(7)\quad \alpha_i = \alpha_{i0} + \alpha_{i1} low + \alpha_{i2} t + \alpha_{i3} low \cdot t + \sum_{j=1}^{n} \phi_{ij} \left(\ln adv_j - \sum_{j=1}^{n} w_j \ln p_j \right) + \sum_{m=2}^{3} \psi_{im} D_m .$$

The adding-up property implies that $\Sigma_i \alpha_{i0} = 1$, $\Sigma_i \alpha_{i1} = \Sigma_i \alpha_{i2} = \Sigma_i \alpha_{i3} = \Sigma_i \phi_{ij} = \Sigma_i \psi_{im} = 0$. The advertising elasticities, a_{ij}, are derived in Appendix 1 and calculated as

$$(8)\quad a_{ij} = \frac{1}{w_i} \left(\phi_{ij} - \beta_i \sum_{k=1}^{n} \phi_{kj} \ln p_k \right) .$$

The price, total expenditure, and advertising elasticities in the second stage (6) and (8) are conditional on the total expenditures allocated to non-alcoholic beverages in stage one. Carpentier and Guyomard (2001) provide formulas for approximating the unconditional price and expenditure elasticities from the estimated conditional elasticities; however, we did not pursue their approach. We only note that if the advertising elasticity in stage one is zero, the unconditional and conditional elasticities are numerically identical.

Data and empirical implementation

Prices for non-alcoholic beverages, alcoholic beverages, food, and other non-durables and services are included in the demand function at stage one. Furthermore, advertising expenditures for non-alcoholic beverages and total expenditures on non-durables and services are added as independent variables. The data on prices and the total expenditures were provided by Statistics Norway.

Four groups of beverages are specified at stage two: whole milk, lower fat milk, hot drinks, and cold drinks. The lower fat milk group consists of nonfat and low fat milk. The cold drinks group consists of fruit juices, soft drinks, light beer, and mineral water. The hot drinks group consists of coffee, tea, and cocoa. The prices and quantities of dairy products were obtained from the Norwegian Dairy Cooperative while the corresponding data for various hot and cold drinks were obtained from the Norwegian Social Science Data Services. The price and quantity observations are four-month data spanning the 1975 to 1995 period, which includes 63 observations. The prices of the elementary beverages were aggregated as Divisia price indices.

ACNielsen collected the advertising data. The data set was checked against available marketing data from the dairy cooperative, and the correspondence was good. The data cover advertising in newspapers, TV, radio, movies, and boards. Unfortunately, the advertising expenditures are only available on an annual basis. The expenditures were divided by three to calculate advertising expenditures in each four-month period. Possible fluctuations are smoothed away by this procedure. If there were substantial variations in the advertising activities throughout the year, the smoothing may bias our results. We discussed possible distributions of the advertising expenditures with our contact group in the dairy cooperative; however, they could not suggest any better distribution indicating that no pulsing strategy has been used in advertising milk. Therefore, we believe that a uniform distribution of advertising expenditures over the year is a reasonably good approximation. Fluid milk is mainly advertised as one good and the same advertising variable was used for lower fat and whole milk.

As discussed in the graphical analysis, we treat milk price as exogenous. The prices of hot drinks and in some cases cold drinks are deter-

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mined at the world market and these prices are also treated as exogenous. Furthermore, work by Bronsard and Salvas-Bronsard (1984) suggests that price endogeneity is relatively unimportant in demand-system estimation when the goods in question represents a small share of income, as is the case for non-alcoholic beverages. Advertising expenditures and total non-alcoholic expenditures are also treated as exogenous as in most previous studies. The first-stage model (3) was estimated by ordinary least squares. The LSQ procedure in the TSP program was used to compute iterative seemingly unrelated regressions in stage two. As is customary, one equation was dropped from estimation.

Autocorrelation is frequently a serious problem in studies using time-series data. In the second stage, it was tested for by using first- and third-order Breusch-Godfrey tests. These tests are calculated as

$$\text{(9)} \quad \hat{u}_{i,t} = \mathbf{x}_t' \beta + \rho\, \hat{u}_{i,t-1} + \upsilon_{i,t} \text{ and}$$
$$\hat{u}_{i,t} = \mathbf{x}_t' \beta + \rho_1 \hat{u}_{i,t-1} + \rho_2 \hat{u}_{i,t-2} + \rho_3 \hat{u}_{i,t-3} + \upsilon_{i,t},$$

where $\mathbf{x}_t$ is the t-th observation of the vector of regressors, $\hat{u}_i$ is the error term associated with estimation of the i-th equation and υ_i is assumed to have a normal distribution with a zero mean and constant variance. The average number of parameters in each estimated equation is used to calculate the F statistic for the tests. The tests are performed for each equation and jointly for the estimated demand system. The single-equation tests are only strictly relevant in a single-equation framework, and the results can only be interpreted as indicators of autocorrelation in a system context.

Estimation results

Aggregate model

Expenditure, advertising, and uncompensated price elasticities for non-alcoholic beverage demand are reported in Table 1. Of particular interest is the response to advertising. No significant response to advertising is found in the first stage. This result indicates that non-alcoholic beverage advertising has been unsuccessful in increasing the overall market size for non-alcoholic beverages. Kinnucan et al. (2001) found a corresponding result for the US. The expenditure elasticity is 0.26 and the own-price elasticity is –0.48. None of the cross-price elasticities is statistically significant at the 5% level. The trend is not significant. As expected, there is a significant positive seasonal effect (D_2) during May to August. The R^2 value shows that the model explains 75 percent of the variation in the aggregate demand for non-alcoholic beverages.

Autocorrelation in the AID model

The P values of the Breusch-Godfrey tests (9) for autocorrelation are shown in Table 2. A P

Table 1. First-stage elasticities, other parameter estimates, and test statistics[1].

Elasticities					
Expenditure	Advertising	$P_{NON\ ALCOHOLIC}$	$P_{ALCOHOLIC}$	P_{FOOD}	P_{OTHER}
0.26*	0.00	–0.48*	–0.10	0.21	0.13
(1.97)	(0.09)	(–3.94)	(–1.22)	(0.99)	(0.65)
Trend	D_2	D_3	R^2	DW	
0.03	0.04*	–0.00	0.75	1.75	
(0.81)	(4.13)	(–0.09)			

[1] In parentheses, t ratios. A single asterisk indicates significance at the 5% level.

Table 2. Tests for autocorrelation, P values[1].

	System	Whole milk	Cold drinks	Hot drinks
AR(1)				
Level	0.00	0.00	0.83	0.91
1st difference	0.00	0.45	0.00	0.00
3rd difference	0.00	0.00	0.09	0.14
$r_{ij}^* = r_{ij} - r_{in}$	0.27	0.38	0.13	0.07
AR(3)				
$r_{ij}^* = r_{ij} - r_{in}$	0.23	0.31	0.20	0.11

[1] Note: α_0 is fixed in these tests.

value shows the lowest significance level at which the null hypothesis of no autocorrelation can be rejected. It is rejected at the 5% level if the *P* value is less than 0.05.

When our model was estimated on level form, we found first-order autocorrelation, AR(1), in the whole milk equation as well as in the system. First, we tried to remove the autocorrelation by estimating the model on first- and third-difference form. Third differencing did not change the pattern of autocorrelation. On the other hand, first differencing quite successfully removed AR(1) in the whole milk equation. However, autocorrelation was introduced into the other two equations and did not disappear from the system.

Given these results, we followed Piggott et al. (1996) and considered a more general correction for autocorrelation. We assumed the vector of errors in our estimated system was determined by $\mathbf{u_t} = \mathbf{Ru_{t-1}} + \mathbf{v_t}$ where the $\mathbf{v_t}$s are independent $N(0,\Sigma)$ random vectors, and $\mathbf{R}$ is an n by n matrix of unknown parameters. When this assumption is used, adding up has typically been imposed by forcing $\mathbf{R}$ to be diagonal, with the diagonal elements, r_{ii}, restricted to be the same for each equation. However, our previous test results indicate that it is unlikely that the diagonal elements are identical. Consequently, we relaxed this assumption and used the full $\mathbf{R}$-matrix allowing that the off-diagonal elements are non-zero and the diagonal elements are different. Berndt and Savin (1975) showed that maximum-likelihood estimation of such a system satisfies invariance provided the $\mathbf{R}$-matrix is appropriately restricted. We followed Piggott et al. (1996) and restricted the $\mathbf{R}$-matrix such that $\iota'\mathbf{R}^* = 0$ where $\mathbf{R}^*$ is an n by $(n-1)$ matrix with elements $r_{ij}^* = r_{ij} - r_{in}$. Under the assumption that the $\mathbf{v_t}$s are normally distributed, our results from the non-linear iterative seemingly unrelated regressions are equivalent to the maximum-likelihood estimates (Berndt and Savin 1975). This correction for autocorrelation was quite successful in removing the first-order autocorrelation. Third-order autocorrelation was also rejected and the remaining results were obtained within this corrected model.

Table 3. Results of Wald tests at stage two.

Restrictions	χ^2	# of rest.	P value
No advertising effects	33.94	9	0.00
No trend effects	33.10	3	0.00
No seasonal effects	162.97	6	0.00
No low fat effects	210.91	6	0.00

Specification tests

The χ^2 values, the number of restrictions for each null hypothesis, and the *P* values of Wald tests, concerning hypotheses of no advertising, no trend, no seasonal, and no low fat effects, are presented in Table 3. All these hypotheses are rejected at the 5% level of significance. The rejection of no advertising effects demonstrates

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that advertising indeed has an effect on the expenditure shares in the second stage.

Elasticities and the demand response to advertising

The estimated parameters are presented in Appendix 2. There is a significant negative trend against whole milk. This trend increased after the introduction of low fat milk in 1985. There is also a significant and positive trend in favor of cold drinks and several significant seasonal effects.

Table 4 reports uncompensated price, advertising, and total expenditure (*E*) elasticities. The elasticities are calculated at the mean values of the variables. Advertising for fluid milk has a significant and positive effect on whole milk demand and a significant and negative effect on the demand for lower fat milk; i.e., the advertising activities apparently delayed the transition from whole to lower fat milk. The elasticities indicate that a 20 percent increase in advertising for fluid milk has increased the sale of whole milk by approximately 1 percent and reduced the sales of lower fat milk by approximately 1.4 percent. Since the average annual per capita sales of whole and lower fat milk were 95 and 59 liters, respectively, the net effect of advertising on the total demand for fluid milk is low. The own-advertising elasticities for cold and hot drinks are positive but not significantly different from zero.

Using the numbers in Table 4, we calculated the share weighted own-advertising elasticity for the combined fluid milk group to be 0.0008. This low value compares reasonably well with Goddard et al.'s (1992) estimate for Canada and Kinnucan et al.'s (2001) estimate for the US, which also were found using demand systems. The other own-advertising elasticities reported in Table 5 were found by single-equation methods and they are in most cases substantially higher indicating that single-equation models may overstate the effects of advertising.

An advertising elasticity of 0.0008 suggests that additional advertising would not have been profitable. For example, in 1995 the total domestic consumption of fluid milk (Q_2 in Fig. 3) was 622 million liters, the consumer price (P_2 in Fig. 3) approximately NOK 6.00 per liter, and the advertising expenditures approximately NOK 20 million. As argued above, the consumer price is set by the government and fixed and there are no induced price effects of milk advertising. Furthermore, as a first approximation, we set the world market price (P_1 in Fig. 3) to zero and assume that the opportunity cost of advertising expenditure is zero. Under these assumptions, a 1 percent increase in advertising expenditures (NOK 200,000) would increase the demand for milk by about 5,000 liters with a value of NOK 30,000 resulting in a direct loss of NOK 170,000. Given a positive world market price and a positive opportunity cost the loss would be even larger.

The estimated advertising elasticities (Table 4) confirm the importance of allowing for cross-commodity advertising effects. The demand for milk is affected by advertising for cold and hot drinks and the cross-advertising elasticities are numerically high; however, there are substantial standard errors associated with them. There are significant and negative cross-advertising effects of advertising for cold and hot drinks on the demand for lower fat milk. A positive cross-advertising elasticity of advertising for hot drinks on the demand for whole milk is also found. Similar and rather surprising positive cross effects were also found in Goddard et al. (1992) and Kinnucan et al. (2001). The effects of milk advertising on the demand for other beverages are insignificant.

The conditional own-price elasticities are, as expected, negative. They are also significantly different from zero, with the exception of whole milk. The numerical values are around –0.5 for the other groups of beverages, indicating price-inelastic demand. Most of the cross-price elasticities are significant and we have gross substitutes as well as gross complements. The compensated elasticities, which are not presented in

Table 4. Uncompensated price, advertising, and total expenditure elasticities. Mean shares and goodness of fit values[1].

	Uncompensated price				Advertising					
	1	2	3	4	1 and 2	3	4	E	w	R^2
1: Whole milk	–0.14	0.29*	0.21*	0.15*	0.05*	0.09	0.28*	–0.51*	0.23	0.98
	(–1.37)	(4.35)	(2.09)	(2.71)	(2.36)	(1.95)	(3.79)	(–2.73)		
2: Lower fat milk	–0.02	–0.68*	–0.40	–0.26*	–0.07*	–0.25*	–0.35*	1.36*	0.16	0.99
	(–0.17)	(–4.52)	(–1.93)	(–3.11)	(–1.99)	(–2.51)	(–2.87)	(7.24)		
3: Cold drinks	–0.34*	–0.21*	–0.59*	–0.40*	–0.01	0.11	–0.09	1.56*	0.34	0.91
	(–6.38)	(–2.53)	(–5.24)	(–8.01)	(–0.78)	(1.91)	(–1.21)	(14.29)		
4: Hot drinks	–0.31*	–0.16*	–0.47*	–0.45*	0.02	–0.08	0.09	1.40*	0.26	0.97
	(–5.74)	(–3.14)	(–5.92)	(–7.83)	(1.08)	(–1.12)	(0.90)	(10.07)		

[1] A single asterisk indicates significance at the 5% level. *t* ratios in parentheses.

Table 5. Some estimated advertising elasticities for fluid milk.

Reference	Elasticity	Location	Data period
Kinnucan and Belleza (1991)	0.044	Ontario, Canada	1973–1984
Goddard et al. (1992)	0.002	Ontario, Canada	1971–1984
Kinnucan and Venkateswaran (1994)	0.000–0.031	Ontario, Canada	1973–1987
Reberte et al. (1996)	0.000–0.055	New York	1986–1992
Lenz et al. (1998)	0.014–0.088	New York	1986–1995
Kamp and Kaiser (1999)	0.049–0.067	New York	1986–1995
Tomek and Kaiser (1999)	0.029	United States	1976–1997
Chung and Kaiser (1999)	0.058	New York	1986–1995
Kinnucan et al. (2001)	0.003	United States	1970–1994
The present study	0.001	Norway	1975–1995

the table, show that none of the beverages are net complements. The expenditure elasticities are significant and positive, except for whole milk, which appears to be an inferior good within the second stage.

Conclusions

Aggregate demand for non-alcoholic beverages is unresponsive to advertising expenditures, suggesting that advertising has not increased the market size for non-alcoholic beverages. The allocation of beverage expenditures to the various non-alcoholic beverages is, however, affected. There are different effects of generic advertising on the demand for whole and lower fat milk, indicating that these beverages are better treated separately. Advertising for fluid milk has a significant and positive effect on whole milk's expenditure share and a significant and negative effect on the expenditure share of lower fat milk; i.e., the generic advertising activities have probably delayed the transition from whole to lower fat milk. The net effect of milk advertising on the total fluid milk demand is low with an own-advertising elasticity for the combined fluid milk group of 0.0008. Given fixed prices, increased advertising will not be profitable for the producers.

We found several cross-commodity effects. There are significant and negative cross-advertising effects of advertising for cold and hot drinks on the demand for lower fat milk. These results demonstrate that successful advertising for products such as carbonated soft drinks may

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have a large impact on fluid milk demand. The positive effect of advertising for hot drinks on the whole milk demand indicates that there also may be complementary relationships in advertising. The effects of milk advertising on the demand for other beverages are insignificant. The results demonstrate that a demand system approach is useful for studying the effects of generic fluid milk advertising.

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Appendix 1

Derivation of advertising elasticities

For simplicity, we neglect the dummy variables and the trend and re-write equation (7) as

(A1) $$\alpha_i = \alpha_{i0} + \sum_{j=1}^{n} \phi_{ij} \left(\ln adv_j - \sum_{j=1}^{n} w_j \ln p_j \right) .$$

Substituting equations (5) and (A1) into equation (4) yields

(A2) $$\begin{aligned} w_i = {} & \alpha_{i0} + \sum_{j=1}^{n} \phi_{ij} \left(\ln adv_j - \sum_{j=1}^{n} w_j \ln p_j \right) + \sum_{j=1}^{n} \gamma_{ij} \ln p_j + \beta_i \ln x - \beta_i \alpha_0 - \beta_i \sum_{k=1}^{n} \alpha_{k0} \ln p_k \\ & - \beta_i \sum_{k=1}^{n} \sum_{j=1}^{n} \phi_{kj} \left(\ln adv_j - \sum_{j=1}^{n} w_j \ln p_j \right) \ln p_k - \frac{1}{2} \beta_i \sum_{k=1}^{n} \sum_{j=1}^{n} \gamma_{kj} \ln p_k \ln p_j . \end{aligned}$$

By definition $q_i = w_i x / p_i$ where w_i is given by equation (A2) and the other variables are as previously defined. Using the chain rule, the advertising elasticities, a_{ij}, are calculated as

(A3) $$a_{ij} = \left(\frac{\partial q_i}{\partial \ln adv_j} \cdot \frac{\partial \ln adv_j}{\partial adv_j} \cdot \frac{adv_j}{q_i} \right) = \frac{x}{p_i} \left(\phi_{ij} - \beta_i \sum_{k=1}^{n} \phi_{kj} \ln p_k \right) \frac{1}{adv_j} \frac{adv_j}{q_i}$$

or equation (8).

Appendix 2

Estimated parameters[1].

		Whole milk (i = 1)	Cold drinks (i = 3)	Hot drinks (i = 4)
α_0	–4.815*			
	(–2.58)			
α_{i0}		1.882*	–0.796	–0.197
		(3.72)	(–1.89)	(–1.21)
α_{i1}		0.186*	0.021	0.003
		(6.04)	(0.36)	(0.06)
α_{i2}		–0.004*	0.004*	–0.002
		(–5.49)	(3.59)	(–1.93)
α_{i3}		–0.006*	–0.000	–0.000
		(–8.20)	(–0.26)	(–0.46)
ψ_{i2}		–0.002	0.042*	–0.018*
		(–0.60)	(6.35)	(–3.36)
ψ_{i3}		0.014*	–0.001	0.002
		(3.79)	(–0.09)	(0.32)
γ_{i1}		–0.574*	–	–
		(–3.47)		
γ_{i3}		0.302*	0.003	–
		(2.18)	(0.03)	
γ_{i4}		0.147*	–0.199*	0.111*
		(3.44)	(–7.93)	(3.81)
ϕ_{i1}		0.011*	–0.004	0.005
		(2.36)	(–0.76)	(1.08)
ϕ_{i3}		0.016	0.042	–0.019
		(1.43)	(1.95)	(–1.06)
ϕ_{i4}		0.070*	–0.035	0.022
		(3.91)	(–1.24)	(0.87)
β_i		–0.354*	0.191*	0.104*
		(–8.08)	(5.12)	(2.86)
ρ_{i1}		0.722*	–0.028	0.178
		(7.31)	(–0.25)	(1.91)
ρ_{i3}		0.509*	0.517	–0.417
		(2.13)	(1.74)	(–1.50)
ρ_{i4}		0.515	0.763*	–0.538
		(1.91)	(2.08)	(–1.66)

[1] *t* ratios are in parentheses. A single asterisk indicates significance at the 5% level. The parameters for the equation lower fat milk are not estimated ($i = 2$).

Essay 3

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Forecasting ability of theory-constrained two-stage demand systems

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Summary

Demand models are commonly used to forecast effects of policy changes and two-stage demand systems are frequently used when disaggregated food items are involved. A two-stage system implies interconnections between the stages. These interconnections can be modelled to make unconditional forecasts, or the second stage can be modelled separately to make conditional forecasts. We compare conditional and unconditional elasticity-based and direct statistical forecasts. For our data, conditional forecasts are superior to unconditional forecasts and forecasts derived from elasticities are superior to direct statistical forecasts. Imposition of the homogeneity and symmetry restrictions of consumer theory does not improve the forecasts.

Keywords: dairy demand, demand system, forecasting, two-stage budgeting

JEL classification: Q11

1. Introduction

Forecasts of the demand for disaggregate food products are of interest for agricultural producers, the food processing industry, and policy makers. There are different approaches to forecasting. Forecasts made by models not formally derived from economic theory such as ARIMA or VAR models may be good for pure forecasting purposes; however, they are not very useful for forecasting the effects of price or income changes. Forecasting models derived directly from economic theory are more useful for policy purposes. Kastens and Brester (1996) (hereafter referred to as K&B) used out-of-sample forecasts to select among demand systems for food products. Using the root mean square error (RMSE) criterion, they found that forecasts derived from elasticities were superior to direct statistical forecasts. Moreover, imposition of homogeneity and symmetry improved the forecasts, even when these restrictions were rejected by statistical tests. One objective of this paper is to study whether forecasts improve when homogeneity and symmetry restrictions are imposed.

A second objective is to compare elasticity-based forecasts with direct statistical forecasts. The direct statistical forecasts are the quantities predicted directly by the model, whereas the elasticity-based forecasts are calculated by using the estimated elasticities of the model.

Third, we look at disaggregated commodities. Following usual practice, we assume weak separability and estimate a two-stage model. In stage 1, the demands for non-alcoholic beverages, cheeses, other foods and non-foods are estimated. In stage 2, one non-alcoholic beverages subsystem (consisting of fluid milk, carbonated soft drinks, juices and other cold drinks) and one cheese subsystem (consisting of standard cheeses, soft cheeses, specialty cheeses and whey cheeses)[1] are estimated. As discussed in Edgerton (1997), price and expenditure changes for goods in different subsystems do affect each other and these changes may be important for the forecasting ability of the model. For example, in a two-stage system, consisting of one system describing the demand for broader aggregates (stage 1) and one beverage subsystem (stage 2), a change in the price of fluid milk directly affects the demand for fluid milk within the beverage subsystem. In addition, the price change causes a change in the price of beverages at stage 1. This change causes a change in the demand for beverages and, thereby, the total expenditure allocated to the beverage subsystem. The change in total expenditure causes an indirect change in the demand for fluid milk. The total effect of the price change of fluid milk is the sum of the direct and indirect effects. The total effect is called the unconditional effect and the direct effect is called the conditional effect. We compare unconditional and conditional direct statistical forecasts and unconditional and conditional elasticity-based forecasts using the expressions for unconditional elasticities developed in Carpentier and Guyomard (2001). For example, the unconditional statistical forecasts for fluid milk use the first-stage predicted total expenditure for non-alcoholic beverages in the second-stage non-alcoholic beverage subsystem, whereas the conditional statistical forecasts neglect this first-stage forecast. In the conditional forecasts, non-alcoholic beverage expenditure is forecast by an ARIMA model using only the information within the second-stage beverage subsystem. The conditional and unconditional elasticity-based forecasts are based on the conditional and unconditional elasticities, respectively.

2. The AID system and forecasting

Following Edgerton (1997) and Carpentier and Guyomard (2001), Deaton and Muellbauer's (1980) almost ideal demand (AID) system is used. In the

1 'Standard cheeses' include most of the hard cheeses. 'Specialty cheeses' consist of domestically produced semi-soft cheeses and relatively expensive imported semi-soft and hard cheeses. 'Whey cheeses' are brown and sweetish cheeses that are popular in Norway.

stochastic version, the ith good's expenditure share in period t, $w_{i,t}$, is given by

$$w_{i,t} = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_{j,t} + \beta_i \ln\left(\frac{x_t}{P_t}\right) + u_{i,t} \tag{1}$$

where p_j denotes the price per unit of good j, x is the per capita expenditure on the goods included in the system, u_{it} is a stochastic error term, and $\ln P$ is a price index defined by

$$\ln P_t = \alpha_0 + \sum_{k=1}^{n} \alpha_k \ln p_{k,t} + \frac{1}{2} \sum_{k=1}^{n} \sum_{j=1}^{n} \gamma_{kj} \ln p_{k,t} \ln p_{j,t}. \tag{2}$$

Adding-up, zero-degree homogeneity of demand in prices and total expenditure, and symmetry require that

$$\begin{aligned} &\sum_{i=1}^{n} \alpha_i = 1, \quad \sum_{i=1}^{n} \beta_i = \sum_{i=1}^{n} \gamma_{ij} = 0 \,\forall j && \text{(adding-up)} \\ &\sum_{j=1}^{n} \gamma_{ij} = 0 \,\forall i && \text{(homogeneity)} \\ &\gamma_{ij} = \gamma_{ji} \,\forall i, j && \text{(symmetry).} \end{aligned} \tag{3}$$

Adding-up is always imposed whereas homogeneity and symmetry may or may not be imposed.

Demand shifters are introduced in the intercepts in equations (1) and (2):

$$\alpha_i = \alpha_{i0} + \phi_i \ln t + \varphi_{i2} D_{2,t} + \varphi_{i3} D_{3,t} \tag{4}$$

where t is a trend variable taking the value of one in the first 4-month period of 1978, two in the second period, and so on. D_2 and D_3 are seasonal dummy variables where D_2 takes the value of one in the second 4-month period and zero otherwise, and D_3 takes the value of one in the third 4-month period and zero otherwise.

To maintain adding-up, the following restrictions are imposed:

$$\sum_{i=1}^{n} \alpha_{i0} = 1, \qquad \sum_{i=1}^{n} \phi_i = \sum_{i=1}^{n} \varphi_{i2} = \sum_{i=1}^{n} \varphi_{i3} = 0. \tag{5}$$

Once the parameters of equations (1)–(5) have been estimated, we can take prices and total expenditure as predetermined at time t and calculate the forecast of the expenditure share, $\hat{w}_{i,t}$. Given this forecast, the direct statistical forecast of the quantity is calculated as

$$\hat{q}_{i,t} = \hat{w}_{i,t} x_t / p_{i,t}. \tag{6}$$

The elasticities of demand with respect to price, e_{ij}, total expenditure, E_i, trend, Et_i, and the seasonal effects, Ed_{ir}, are calculated as

$$e_{ij} = \theta_{ij} + \frac{\gamma_{ij}}{w_i} - \frac{\beta_i}{w_i}\left(\alpha_{j0} + \phi_j \ln t + \varphi_{j2} D_2 + \varphi_{j3} D_3 + \sum_{k=1}^{n} \gamma_{jk} \ln p_k\right) \tag{7}$$

$$E_i = 1 + \frac{\beta_i}{w_i} \tag{8}$$

$$Et_i = \frac{1}{w_i}\left(\phi_i - \beta_i \sum_{k=1}^{n} \phi_k \ln p_k\right) \tag{9}$$

$$Ed_{ir} = \frac{1}{w_i}\left(\varphi_{ir} - \beta_i \sum_{k=1}^{n} \varphi_{kr} \ln p_k\right) \tag{10}$$

where θ_{ij} is the Kronecker delta with values $\theta_{ij} = -1$ for $i = j$ and zero otherwise, and the subscripts denoting time are suppressed. The trend elasticity, Et_i, shows the percentage change in demand for good i when the trend variable changes by 1 per cent. Consequently, the relative change in demand for good i between two consecutive 4-month periods is equal to Et_i/t_{t-1}. Ed_{i2} and Ed_{i3} give the percentage differences in consumption of commodity i between the first and second and the first and third 4-month periods, respectively.[2]

The approach described in K&B is followed for developing the elasticity-based forecasts. They start with the general demand function

$$q_i = f_i(p_1, \ldots, p_n, x) \tag{11}$$

where q_i is the quantity of good i. Taking the total differential of equation (11), reformulating the expression to relative changes, and approximating the result in discrete time yields the forecast quantities

$$\hat{q}_{i,t} = \left[\sum_{j=1}^{n} e_{ij}\left(\frac{p_{j,t} - p_{j,t-1}}{p_{j,t-1}}\right) + E_i\left(\frac{x_t - x_{t-1}}{x_{t-1}}\right)\right] q_{i,t-1} + q_{i,t-1}. \tag{12}$$

Including the trend elasticities and seasonal effects in the demand function (11), the forecast equation (12) becomes

$$\hat{q}_{i,t} = \left[\sum_{j=1}^{n} e_{ij}\left(\frac{p_{j,t} - p_{j,t-1}}{p_{j,t-1}}\right) + E_i\left(\frac{x_t - x_{t-1}}{x_{t-1}}\right) + Et_i\left(\frac{1}{t_{t-1}}\right)\right] q_{i,t-1} + q_{i,t-1}$$
$$+ Ed_{i2} q_{i,t-1} D_{2t} + (Ed_{i3} - Ed_{i2}) q_{i,t-2} D_{3t} - Ed_{i3} q_{i,t-3} D_{1t} \tag{13}$$

where $Ed_{i2}q_{i,t-1}D_{2t}$ is the difference in demand for good i between seasons 1 and 2, $(Ed_{i3} - Ed_{i2})q_{i,t-2}D_{3t}$ is the difference between seasons 2 and 3, and $Ed_{i3}q_{i,t-3}D_{1t}$ is the difference between seasons 3 and 1. The seasonal dummy variable D_1 takes the value of one in the first 4-month period, zero otherwise, and is included to ensure that the total seasonal effects over a year sum to zero such that the forecasts stay on the regression line. K&B made one period out-of-sample forecasts for 44 years using annual updating of the model. We use 4-month data for the 1978–2001 period and we consider it to be fairly restrictive to forecast only one period ahead before the model is updated. Consequently, we make out-of-sample forecasts for nine periods,

2 The model is based on 4-month observations, which is rather uncommon. A 4-month observation period is used because the dairy industry uses a 4-month reporting as well as forecasting period.

and after the first period the observed quantities are replaced by the forecast quantities in equation (13).

K&B made three types of forecasts: direct statistical forecasts with and without homogeneity and symmetry restrictions and elasticity-based forecasts calculated from models with homogeneity and symmetry restrictions. They used the elasticity estimates evaluated at the sample means of the variables. However, in our case, the demand and expenditure shares have changed substantially over the sample period and the use of the elasticities calculated at the last values of the data may provide forecasts that are more accurate. Therefore, we also make elasticity-based forecasts using the elasticities calculated at the average values of the data over the 3 year period prior to the forecasts.[3]

K&B estimated a one-stage demand system. We estimate a two-stage system and refer to our forecasts, made within each (weakly separable) demand system, as conditional forecasts. We make four types of conditional forecasts.

First, conditional statistical unrestricted (CSU) forecasts. Each system is estimated using equations (1)–(5) without imposing homogeneity or symmetry restrictions and the forecasts are made using equation (6).

Second, conditional statistical restricted (CSR) forecasts. These are as for CSU, but homogeneity and symmetry restrictions are imposed.

Third, conditional elasticities evaluated at mean values (CEM) forecasts. Each system is estimated using equations (1)–(5) with homogeneity and symmetry imposed, the elasticities are calculated according to equations (7)–(10) using the sample means of the variables, and the elasticities are inserted into equation (13) to make the forecasts.

Fourth, conditional elasticities evaluated at last values (CEL) forecasts. These are as for CEM, but the elasticities are evaluated at the average values of the expenditure shares, prices and trend for the 1996–1998 period.

When we make conditional forecasts within the beverage and cheese subsystems at stage 2, we need to forecast the total expenditure allocated to these food categories. The advantage of estimating a weakly separable subsystem is that we need only data for prices and quantities of the goods included in the subsystem and the total expenditure allocated to non-alcoholic beverages and cheeses are forecast by ARIMA models as described below.

3. Unconditional forecasting and elasticities in two-stage demand systems

Two-stage budgeting implies that changes in prices and total expenditure in one subsystem affect other subsystems (only) through the total expenditure terms. We investigate the importance of including these effects by comparing

3 The choice of the years 1996–1998 to represent the 'last' values is, to some extent, arbitrary. However, we chose the nine periods prior to the forecasting period because we make forecasts nine periods ahead.

the conditional forecasts described above with unconditional forecasts based on information from all the estimated weakly separable systems.

To derive the unconditional elasticity-based forecasts, we follow Carpentier and Guyomard (2001), who derived formulae for approximating unconditional elasticities in a two-stage demand model. In the case where all the second-stage elementary commodities belong to the same first-stage commodity group G, the relationships may be written as

$$E_i = E_{(G)i} E_G \tag{14}$$

and

$$e_{ij} = e_{(G)ij} + w_{(G)j}\left(\frac{1}{E_{(G)j}} + e_{GG}\right) E_{(G)i} E_{(G)j} + w_{(G)j} w_G E_G E_{(G)i} (E_{(G)j} - 1) \tag{15}$$

where E_i is the unconditional expenditure elasticity for good i, $E_{(G)I}$ is the estimated conditional expenditure elasticity, E_G is the expenditure elasticity for group G, e_{ij} is the unconditional (uncompensated) price elasticity, $e_{(G)ij}$ is the estimated conditional price elasticity, $w_{(G)j}$ is the within-group expenditure share, e_{GG} is the own-price elasticity of group G, and w_G is the expenditure share of group G.

In the case where elementary commodity i belongs to the first-stage commodity group G and elementary commodity j belongs to the first-stage commodity group H, equation (15) is replaced by

$$e_{ij} = w_{(H)j} e_{GH} E_{(G)i} E_{(H)j} + w_{(H)j} w_H E_G E_{(G)i} (E_{(H)j} - 1). \tag{16}$$

Trend and seasonal effects in one subsystem also affect other subsystems through the total expenditure terms. The unconditional trend elasticities and seasonal effects are derived in Appendix 1. Let Et_i be the unconditional trend elasticity for good i in group G, $Et_{(G)i}$ the corresponding conditional trend elasticity, and Et_G the trend elasticity of group G. The unconditional trend elasticity for good i in group G is calculated as $Et_i = Et_{(G)i} + E_{(G)i} Et_G$. Furthermore, the percentage changes in demand when moving from the first to the second and the second to the third 4-month periods are $Ed_{i2} = Ed_{(G)i2} + E_{(G)i} Ed_{(G)2}$ and $Ed_{i3} = Ed_{(G)i3} + E_{(G)i} Ed_{(G)3}$, where $Ed_{(G)ir}$ is the conditional seasonal effect, and $Ed_{(G)r}$ the seasonal effect for group G in season $r = 2, 3$.

We make four types of unconditional forecasts corresponding to the four types of conditional forecasts described above. The unconditional and conditional forecasts are identical for stage 1 and we make only unconditional forecasts for the second-stage beverages and cheeses subsystems.

First, unconditional statistical unrestricted (USU) forecasts are made without imposing homogeneity and symmetry restrictions. To forecast the total expenditures allocated to the beverage and cheese subsystems, the first-stage forecasts of the quantity of beverages and the quantity of cheeses, made by using equation (6), are multiplied by the price of beverages and the price of cheeses. These forecast first-stage expenditures are used as total expenditures in the second-stage systems (1)–(5) to make forecasts for the four beverages and the four cheeses.

Second, unconditional statistical restricted (USR) forecasts are made as for the USU, but homogeneity and symmetry restrictions are imposed.

Third, unconditional elasticities at mean (UEM) values forecasts are evaluated. Each system is estimated by using equations (1)–(5) with homogeneity and symmetry imposed, the conditional elasticities evaluated at mean values of the data are calculated by using equations (7)–(10), equations (14)–(16) are used to construct the unconditional elasticities, and these elasticities are inserted into equation (13) to make the forecasts.

Fourth, unconditional elasticities evaluated at last (UEL) values are used to make forecasts. These forecasts are constructed as for the UEM, but the elasticities are evaluated at the average values of the expenditure shares, prices and trend for the 1996–1998 period.

4. Data and elasticity estimates

The data set consists of 4-month observations for the 1978–2001 period. The Norwegian dairy co-operative, TINE, provided the price and quantity data for the dairy products until 1997. For later years, we supplemented TINE's data with data obtained from new processors that have entered the market.[4] Hence, the data set covers total consumption of dairy products from domestic and imported sources. The Norwegian Social Science Data Services and the Norwegian Brewers and Soft Drink Producers' Association provided the data for other beverages. Statistics Norway provided data for current and real expenditures on other foods, nondurables and services, as well as the population data used to calculate per capita total expenditures.

Various demand studies (see, for example, Attfield, 1997) have found that nonstationarity of the data may be a problem. When all data series are stationary, the demand system can be estimated using conventional econometric techniques. When all data series are nonstationary but integrated of the same order, the demand equations represent a long-run relationship between prices and shares only if the prices and shares are cointegrated. The expenditure shares and the prices (in logarithmic form) were tested for stationarity using an Augmented Dickey–Fuller (ADF) test including a logarithmic trend and two seasonal dummy variables. The number of lags included in the ADF test may critically affect the outcome of the test and different guidelines have been suggested for the choice of number of lags. We followed the general to specific rule proposed by Hall (1994) and recommended by Maddala and Kim (1998: 78). We started with a generous parameterisation including six lags, tested for the significance of the last lag, and reduced the number of lags iteratively until a significant lag was encountered. Because we did not want to exclude too many lagged terms, the 10 per cent level of significance was used.

4 TINE was a monopolist until the mid-1990s when the government allowed some competition in the dairy market. However, TINE's market share is still above 90 per cent.

The null hypothesis of the ADF test is that there exists a unit root, and hence the series is nonstationary. However, the power of the ADF test is low when the root is close to but below one—an alternative that is plausible (Maddala and Kim, 1998: 100). Hence, to compensate for the testing procedure's possible low power, the 10 per cent level of significance was selected for the unit root tests. The test results show that a unit root was not rejected for any of the expenditure shares. However, a unit root was rejected for three of the prices at stage 1, two of the prices in the beverage subsystem, and two of the prices in the cheese subsystem. Given that we could not reject nonstationarity for the expenditure shares and five of the prices, whereas nonstationarity was rejected for seven of the prices, there is no clear implication for how to proceed.

To investigate the stationarity properties further, we conducted an ADF test on the estimated error terms of equations (1)–(5) allowing for a maximum of six lags and excluding the constant term, the trend and the seasonal dummy variables for the ADF test. The presence of a unit root was rejected for each error term, both in the systems with homogeneity and symmetry restrictions and in the unrestricted systems. These results confirm the existence of long-run demand relationships. Furthermore, all the goods within each subsystem are expected to be close substitutes and in such systems one would expect the existence of long-run relationships between the dependent and independent variables. In light of these results, we proceeded as if the data are stationary. However, some caution should be used when interpreting the results.

Equations (1)–(5) were used to estimate the demand for broader groups of commodities (stage 1), beverages (stage 2a) and cheeses (stage 2b), using the LSQ procedure in TSP. Each system was estimated using the data for the period 1978–1998, whereas the data for 1999–2001 were kept for validating the out-of-sample forecasts. In the first stage, implicit Paasche price indices were constructed by dividing current expenditure by real expenditure. In the second stage, prices were aggregated as Divisia price indices.

The joint hypothesis of homogeneity and symmetry was tested with a likelihood-ratio test, involving seven restrictions. The test statistic is distributed asymptotically as χ^2_7, whose 5 per cent critical value is 14.1. At the first stage, the estimated test statistic is 62.0 and for the cheese system it is 70.6. The corresponding P values are 0.00, thus rejecting homogeneity and symmetry at any reasonable level of significance. Rejections of homogeneity and symmetry are usual in the literature and are also in line with K&B results. For the beverage system, the test statistic is 3.33 and homogeneity and symmetry is not rejected.

Tables A1 and A2 (Appendix 2) show the conditional uncompensated price and total expenditure elasticities calculated using equations (7) and (8)[5] with the homogeneity and symmetry restrictions imposed. Table A1 gives the elasticities calculated at the mean values of the variables as in K&B. Table A2

5 The trend elasticities and the percentage changes in demand as a result of seasonal components may be obtained from the authors.

shows the elasticities evaluated at the average of the 3 years prior to the forecasting period.[6] At stage 1 and stage 2b, there are minor differences between the elasticities evaluated at the mean and at the last values. At stage 2a, the differences are substantial, especially for fluid milk and carbonated soft drinks. The numerical values of the own-price elasticities for fluid milk, carbonated soft drinks and other cold drinks have increased. Furthermore, fluid milk is increasingly becoming an inferior good within the beverage subsystem. Fluid milk has also previously been found to be an inferior good in Norway (Rickertsen and Gustavsen, 2002). The values of several of the cross-price elasticities have also changed. Both sets of elasticities are used for making forecasts as discussed above.

Table A3 (Appendix 2) shows the unconditional price and total expenditure elasticities for beverages evaluated at mean values.[7] The elasticities are calculated by means of equations (14)–(16) and the reported t values are found using 100 bootstrap repetitions. The own-price elasticities are negative and significantly different from zero except for other cold drinks. The cross-price elasticities between fluid milk and carbonated soft drinks are positive and significant indicating gross substitutes. There are significant cross-price elasticities between other foods and also other nondurables and the different beverages, demonstrating that stage 1 effects are important for beverage demand. The unconditional expenditure elasticities are less elastic than the conditional ones. The unconditional own-price elasticities are less elastic for carbonated soft drinks and juices but more elastic for fluid milk and other cold drinks.

Table A4 (Appendix 2) shows the unconditional price and total expenditure elasticities for cheeses evaluated at the mean values. The own-price elasticities are negative and significantly different from zero except for whey cheeses. The more expensive specialty cheeses are the most price elastic. There are significant and positive cross-price elasticities between many of the cheeses suggesting gross substitutes. There are several significant cross-price elasticities between other nondurables and the different cheeses indicating the importance of stage 1 effects. The unconditional total expenditure elasticities are highly inelastic compared with the conditional elasticities and not significantly different from zero.

5. The forecasting ability of the models

We used the eight forecasting models described above to make out-of-sample forecasts for nine periods (3 years), conditional on known prices and total stage 1 expenditures. In the elasticity-based models, $q_{i,t-1}$ in equation (13)

6 Because of the adding-up restrictions, commodity 4 (in Table A1) was dropped from estimation and the parameter estimates of this equation were recovered from the adding-up restrictions. The parameter estimates did not change when an alternative equation was dropped from estimation.

7 The unconditional price and total expenditure elasticities calculated at 1996–1998 values are available from the authors. We note that the differences between the unconditional elasticities evaluated at the mean and at the last values are smaller than for the conditional elasticities.

was assumed to be known only for the first period. For later periods, the quantities forecast for previous periods were used instead of the observed quantities.

In the conditional forecasts, ARIMA models were used to forecast the total expenditure allocated to the beverage and cheese subsystems. To identify the ARIMA model that best fitted the beverage expenditure for the 1978–1998 period, we differentiated the expenditure variable to remove a trend and seasonally differentiated the expenditure to remove the seasonal components. Let $x_{2a,t}$ be the total expenditure on beverages at time t and let $\nu_{2a,t} + \theta\nu_{2a,t-1}$ be a moving average disturbance term. The chosen ARIMA model is $x^*_{2a,t} = 0.44x^*_{2a,t-1} + \nu_{2a,t} + 0.90\nu_{2a,t-1}$, where $x^*_{2a,t} = (1-L)(1-L^3)\ln x_{2a,t}$ and L and L^3 denote the lag and seasonal lag operators. Total cheese expenditure did not show any trend component and we just seasonally differentiated the expenditure variable to make it stationary. Let $x_{2b,t}$ be total cheese expenditure at time t and let $\nu_{2b,t} + \theta\nu_{2b,t-1}$ be a moving average disturbance term. The chosen ARIMA model is $x^*_{2b,t} = 0.93x^*_{2b,t-1} + \nu_{2b,t} + 0.29\nu_{2b,t-1}$ where $x^*_{2b,t} = (1-L^3)\ln x_{2b,t}$. The forecasts obtained for nine periods (1999:1–2001:3) using these models resulted in a root mean squared out-of-sample forecast error (RMSE) of 0.4 for beverage expenditure and 1.1 for cheese expenditure.

Following K&B, we used a test developed by Ashley, Granger and Schmalensee (1980) (AGS) to compare forecasts formally. The AGS test provides a test for the statistical significance of the difference between the RMSE of two competing forecasts. Let $D_t = fe^h_t - fe^\ell_t$, where fe^h_t is the forecast error for the forecast model with the highest RMSE and fe^ℓ_t is the forecast error from the model with the lowest RMSE. If the mean of fe^h_t or fe^ℓ_t is negative, the associated series must be multiplied by -1. Let $S_t = fe^h_t + fe^\ell_t$ and let SM denote the sample mean of S_t. We estimate the regression $D_t = \beta_0 + \beta_1(S_t - SM) + v_t$, where v_t is assumed to be a white-noise disturbance term. The test compares the null hypothesis H_0: $\beta_0 = \beta_1 = 0$ with the alternative H_1: $\beta_0 > 0$ and/or $\beta_1 > 0$. If one coefficient is negative and significant, the test is inconclusive. If one coefficient is negative but insignificant, a one-tailed t-test on the other coefficient can be used. If the β_0 and β_1 estimates are both positive, an F-test is used. Because the F-test does not consider the signs of the coefficient estimates, actual significance levels are only one-fourth of those reported in an F-table, i.e. the probability of obtaining an F-statistic greater than the critical value and having both estimates positive is equal to one-fourth of the significance level normally associated with the critical value.

The results from the competing forecasts are reported in Table 1. This table shows the out-of-sample RMSE after nine periods of forecasts, for our eight different forecast models, and the three different stages. Below each reported RMSE, there are two numbers in parentheses. The first number denotes the number of competing forecasts that are nominally worse, i.e. the number of alternative forecasts in the same row that have a nominally higher RMSE. The maximum is three at stage 1 and seven at stage 2a and stage 2b. The second number denotes the number of forecasts that are significantly worse

Table 1. Out-of-sample forecast RMSE and model rankings after nine periods of forecasts

Commodity	Forecasting models							
	USU	USR	UEM	UEL	CSU	CSR	CEM	CEL
Stage 1[a]								
Non-alcoholic beverages	3.07	1.91	1.71	1.91				
	(0,0)	(1,1)	(3,2)	(2,1)				
Cheeses	5.64	5.96	6.38	6.32				
	(3,2)	(2,0)	(0,0)	(1,1)				
Other foods	5.04	3.79	6.98	7.89				
	(2,2)	(3,2)	(1,1)	(0,0)				
Other nondurables	0.71	0.54	0.99	1.09				
	(2,0)	(3,0)	(1,0)	(0,0)				
Stage 2a								
Fluid milk	22.12	22.29	8.08	8.80	18.55	18.62	7.46	7.45
	(1,0)	(0,0)	(5,4)	(4,4)	(3,0)	(2,0)	(6,6)	(7,5)
Carbonated soft drinks	3.78	3.83	5.55	6.22	5.09	4.92	7.85	5.32
	(7,0)	(6,0)	(2,0)	(1,0)	(4,1)	(5,2)	(0,0)	(3,1)
Juices	32.70	32.89	19.61	19.75	32.09	32.09	14.39	14.93
	(1,0)	(0,0)	(5,5)	(4,2)	(2,2)	(3,3)	(7,7)	(6,6)
Other cold drinks	10.50	12.49	12.03	12.62	12.90	13.14	13.61	12.11
	(7,4)	(4,1)	(6,0)	(3,0)	(2,0)	(1,0)	(0,0)	(5,1)
Stage 2b								
Standard cheeses	14.19	13.03	7.46	7.57	2.62	6.34	8.62	8.61
	(0,0)	(1,0)	(5,1)	(4,0)	(7,7)	(6,6)	(2,0)	(3,0)
Soft cheeses	55.82	97.67	30.65	28.97	29.76	34.74	30.41	28.37
	(1,0)	(0,0)	(3,2)	(6,3)	(5,0)	(2,2)	(4,2)	(7,3)
Specialty cheeses	38.56	49.68	13.17	10.24	8.27	23.90	16.51	13.15
	(1,1)	(0,0)	(4,3)	(6,4)	(7,4)	(2,2)	(3,1)	(5,3)
Whey cheeses	5.31	18.18	5.80	5.58	10.41	12.03	6.88	6.22
	(7,2)	(0,0)	(5,3)	(6,3)	(2,0)	(1,1)	(3,3)	(4,3)

The left and right numbers in parentheses denote the number of other forecasts (in the row) having nominally and statistically higher RMSEs. Statistical significance of the AGS test is at the 10 per cent level. The larger the number in parentheses, the better the forecast.

[a]The conditional and unconditional forecasts at stage 1 are identical.

according to the AGS test. The larger the numbers, the better are the forecasts. The significance level used for these tests is 10 per cent.

Several results follow from Table 1. First, except at stage 1, our RMSEs are considerably higher than the values reported in K&B. There are two likely

Table 2. Unweighted and weighted average ranking of forecasting models

Forecast	Brief description	Unweighted		Weighted[a]	
		Nominal	Statistical[b]	Nominal	Statistical[b]
USU	Unconditional statistical unrestricted	3.13	0.88	3.02	0.36
USR	Unconditional statistical restricted	1.38	0.13	1.98	0.06
UEM	Unconditional elasticities at mean values	4.38	2.25	4.19	2.25
UEL	Unconditional elasticities at last values	4.25	2.00	3.33	1.88
CSU	Conditional statistical unrestricted	4.00	1.75	3.88	1.68
CSR	Conditional statistical restricted	2.75	2.00	3.38	1.85
CEM	Conditional elasticities at mean values	3.13	2.38	3.28	2.87
CEL	Conditional elasticities at last values	5.00	2.75	4.93	2.88

Each average ranking is the average over eight rankings: the four items in each of the two demand systems at stage 2.
[a]The expenditure shares are used as weights.
[b]Rankings established upon differences in RMSEs at the 10 per cent level of significance using the AGS test. The larger the number, the better the forecast.

explanations for our relatively high RMSE. We make forecasts for nine periods, whereas K&B forecast for one period. When forecasting more than one period, the forecast errors accumulate and increase the RMSE. Furthermore, our commodity specification is fairly detailed and includes several goods with small expenditure shares that may be difficult to forecast accurately. Second, contrary to K&B, the imposition of homogeneity and symmetry does not improve the forecasts. Third, there is no clear picture regarding the superiority of the conditional or unconditional forecasts. Fourth, for fluid milk, juices, soft cheeses and specialty cheeses the RMSEs of the statistical models are very high, although the statistical models do very well at stage 1.

The unweighted rankings of stage 2a and stage 2b in Table 1 are summarised in Table 2. Weighted rankings, using the expenditure shares as weights, are also reported. A weighted ranking is more appropriate when it is most important to accurately forecast the demand for products with large expenditure shares. In stage 2a and stage 2b, all the eight forecast models are used, and, in the remaining tables, we compare the forecasts for these two subsystems only. According to each ranking criterion, the best average-ranked forecasts are made by the CEL model. The two best forecasting models are elasticity-based according to all criteria. It is more difficult to see a clear pattern for unconditional than for conditional forecasts. A comparison of the homogeneity and symmetry restricted models with the unrestricted models indicates that the unrestricted models provide the best forecasts in most cases. However, the worst forecasting model is the unconditional statistical model.

The number of statistically different rankings according to the AGS test is summarised in Table 3, which clarifies several essential features. First, the

Table 3. Comparisons between groups of models

Comparison	No. of times that left model is better than right	No. of times that right model is better than left	No. of times that models could not be ranked	Average % drop in RMSE going from right to left model
Conditional forecasts compared with unconditional forecasts				
CSU vs. USU	2	1	5	7.9
CSR vs. USR	5	0	3	13.0
CEM vs. UEM	2	0	6	−0.4
CEL vs. UEL	2	0	6	0.5
Elasticity forecasts compared with statistical forecasts				
UEM vs. USR	5	0	3	18.5
UEL vs. USR	5	1	2	18.8
CEM vs. CSR	3	2	3	5.0
CEL vs. CSR	5	1	2	6.2
Unrestricted statistical forecasts compared with restricted statistical forecasts				
USU vs. USR	3	0	5	8.4
CSU vs. CSR	2	2	4	3.3
Elasticities evaluated at last values forecasts compared with elasticities evaluated at mean values forecasts				
UEL vs. UEM	1	2	5	0.3
CEL vs. CEM	3	1	4	1.2

All rankings at the 10 per cent level of significance using the AGS test.

conditional forecasts are compared with unconditional forecasts. Of the 32 comparisons, 20 are inconclusive, the conditional forecasts are better in 11 of the tests, and the unconditional forecasts are better in only one case. Second, the elasticity-based forecasts are compared with the direct statistical forecasts. The elasticity-based forecasts are better in 18 of the tests, the statistical forecasts are better in four cases, and the tests are inconclusive in 10 cases. Third, unrestricted and restricted statistical forecasts are compared. Unrestricted forecasts are better in five of the tests whereas restricted forecasts are better in two of the tests, and the tests give inconclusive results in nine cases. Finally, forecasts based on elasticities evaluated at last values are compared with elasticities evaluated at mean values. Mean-value forecasts perform better in three cases, last-value forecasts perform better in four cases, and the tests are inconclusive in nine cases.

Another indicator of the performance of a forecasting model is the difference between the observed and forecast value in the last of the forecasting periods. Table 4 shows the percentage differences between the forecast and observed demands in the ninth period. The results indicate similar rankings as in Tables 1 and 2. The direct statistical forecasts usually deviate more than the elasticity-based forecasts and, for some goods, the forecast errors

Table 4. Percentage forecast errors in the last forecast period

Commodity	Forecasting models							
	USU	USR	UEM	UEL	CSU	CSR	CEM	CEL
Stage 1								
Non-alcoholic beverages	−6.1	−3.1	−2.4	−2.9				
Cheeses	10.6	11.7	12.9	12.8				
Other foods	4.8	4.7	−4.6	−5.6				
Other nondurables	−0.6	−0.7	−1.8	−2.0				
Stage 2a								
Fluid milk	37.1	31.8	10.3	12.6	12.9	13.6	8.7	9.1
Carbonated soft drinks	−4.6	−1.5	−0.1	−4.0	10.3	9.7	20.1	12.9
Juices	−45.7	−44.3	−31.4	−32.1	−41.4	−40.9	−19.8	−21.0
Other cold drinks	−2.6	1.0	9.4	2.8	17.3	15.7	28.9	19.2
Stage 2b								
Standard cheeses	15.0	16.6	12.4	12.6	−2.9	7.4	18.9	19.0
Soft cheeses	39.2	101.2	36.0	31.3	−61.9	5.8	34.6	27.0
Specialty cheeses	−34.9	−49.9	−12.2	10.7	2.5	−20.3	−4.3	−3.1
Whey cheeses	6.1	21.0	7.9	5.9	18.3	12.2	14.9	12.3

are very large. It is not evident that the unconditional forecasts are better than the conditional forecasts, and imposing the parametric restrictions of consumer theory does not improve the forecasts.

6. Conclusions

Rather surprisingly, our conditional models produce better forecasts than the unconditional models. This result may be explained in at least two ways. First, two-stage budgeting and the *a priori* imposed separability structure may be inappropriate assumptions for our data set. Second, uncertain estimates at one stage may be carried over to the other subsystem and the unconditional forecasts. The fewer observations that are available, the less likely we are to obtain better estimates using the more complicated two-stage demand system. For applied forecasting, this result suggests that one may, at least in our case, focus on one weakly separable demand system rather than all the stages in a multistage demand system.

Homogeneity and symmetry restrictions are rejected in two out of three demand systems and, contrary to K&B, we do not find that the forecasts improve when these restrictions are imposed. We do not interpret these rejections as rejections of consumer demand theory *per se*. Rather, they raise questions concerning the selected functional form, the selected separability structure, the selected aggregation across individuals and elementary commodities, or possible stationarity problems. Because homogeneity and symmetry are integrated parts of consumer demand theory, we believe that these restrictions should be imposed in any demand system.

Like K&B, we find that elasticity-based models make better forecasts than statistical models. Finally, given our data, it makes little difference whether we use elasticities evaluated at the mean or the last values of the sample, but this may not be the case where elasticities have been strongly trending.

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Appendix 1. Unconditional trend elasticities and unconditional seasonal effects

Consider the allocation of total consumption expenditure, x, between k elementary goods. Define the demand function for good i, q_i, as

$$q_i = f_i(p_1, \ldots, p_k, x, t, D_2, D_3) \tag{A1}$$

where p_i is the unit price of good i, t is a trend, and D_2 and D_3 are seasonal dummy variables denoting the second and third 4-month period of a year.

Two-stage budgeting assumes that the allocation of total expenditure can be divided into two stages. For simplicity, we divide the k goods into two groups, G and H. In the first stage, total expenditure is allocated between these two groups. The first stage is based on an approximation, as it is usually not possible to replace the prices of all the goods in a group with a single price index. The first-stage demand and expenditure functions for group G are given by

$$\begin{aligned} q_G &= f_G(P_G, P_H, x, t, D_2, D_3) \\ P_G q_G &= x_G = g_G(P_G, P_H, x, t, D_2, D_3) \end{aligned} \tag{A2}$$

where P_G is the price index for group G. The second-stage demand function for good i in group G is

$$q_{(G)i} = f_{(G)i}(p_{(G)1}, \ldots, p_{(G)m}, x_G, t, D_2, D_3) \tag{A3}$$

where x_G is the group expenditure and $m < k$. The demand functions (A3) and (A1) are called conditional and unconditional. The two-stage procedure, where stage 1 is defined by (A2) and stage 2 by (A3), approximates the unconditional demand function (A1) so that

$$f_i(p_1, \ldots, p_k, x, t, D_2, D_3) = f_{(G)i}[p_{(G)1}, \ldots, p_{(G)m}, g_G(P_G, P_H, x, t, D_2, D_3), t, D_2, D_3]. \tag{A4}$$

This approximation is good if the preferences are weakly separable and the price indices used do not vary much with utility level (Edgerton, 1997).

Define the unconditional and conditional trend elasticity for good i in group G as $Et_i = \partial \ln f_i / \partial \ln t$ and $Et_{(G)i} = \partial \ln f_{(G)i} / \partial \ln t$. The trend elasticity for group G is defined as $Et_G = \partial \ln f_G / \partial \ln t$. We transform (A4) to the logarithmic form and take the derivative of the resulting equation with respect to $\ln t$ to calculate the unconditional trend elasticity, $Et_i = Et_{(G)i} + E_{(G)i} Et_G$, where $E_{(G)i}$ is the conditional expenditure elasticity of commodity i in group G.

Next, define the unconditional seasonal effect for commodity i between the first and the second 4-month period of a year (i.e. the percentage change in demand for commodity i when moving from the first to the second 4-month period of a year, *ceteris paribus*) by $Ed_{i2} = \partial \ln f_i / \partial D_2$, where ∂D_2 denotes the partial difference between the first and second 4-month period. Correspondingly, the unconditional seasonal effect between the first and the third 4-month period is defined as $Ed_{i3} = \partial \ln f_i / \partial D_3$. We define the conditional seasonal effects for commodity i in group G between the first and the second and the first and the third 4-month period, respectively, as $Ed_{(G)i2} = \partial \ln f_{(G)i} / \partial D_2$ and $Ed_{(G)i3} = \partial \ln f_{(G)i} / \partial D_3$. Finally, the seasonal effects for group G are defined as $Ed_{(G)2} = \partial \ln f_G / \partial D_2$ and $Ed_{(G)3} = \partial \ln f_G / \partial D_3$. We use the same procedure as for the trend but with respect to D_2 and D_3 to obtain $Ed_{i2} = Ed_{(G)i2} + E_{(G)i} Ed_{(G)2}$ and $Ed_{i3} = Ed_{(G)i3} + E_{(G)i} Ed_{(G)3}$.

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Appendix 2. Conditional and unconditional price and expenditure elasticities

Table A1. Conditional uncompensated price and expenditure elasticities calculated at the mean[a]

Commodity	Number	Price				Expenditure
		1	2	3	4	
Stage 1						
Non-alcoholic beverages	1	−0.24	−0.02	−0.26	0.31	0.20
		(−2.88)	(−0.55)	(−3.68)	(3.81)	(3.22)
Cheeses	2	−0.05	−0.39	−0.19	0.52	0.11
		(−0.53)	(−4.79)	(−2.02)	(5.38)	(1.61)
Other foods	3	−0.04	−0.01	−0.56	−0.13	0.74
		(−5.21)	(−3.17)	(−9.02)	(−2.06)	(15.54)
Other nondurables	4	−0.01	−0.00	−0.07	−0.99	1.07
		(−6.11)	(−3.55)	(−6.52)	(−85.21)	(121.40)
Expenditure share		0.020	0.006	0.151	0.823	
Stage 2a						
Fluid milk	1	−0.08	0.23	−0.01	−0.01	−0.13
		(−1.26)	(4.19)	(−0.21)	(−0.45)	(−7.13)
Carbonated soft drinks	2	−0.90	−1.22	−0.16	−0.10	2.38
		(−7.87)	(−12.28)	(−2.72)	(−1.68)	(38.91)
Juices	3	−0.93	−0.13	−0.61	0.08	1.59
		(−6.34)	(−0.92)	(−4.30)	(0.76)	(13.33)
Other cold drinks	4	−1.74	−0.66	−0.02	−0.57	2.99
		(−6.13)	(−2.46)	(−0.09)	(−1.42)	(12.53)
Expenditure share		0.52	0.29	0.13	0.06	
Stage 2b						
Standard cheeses	1	−0.95	0.02	0.30	−0.13	0.76
		(−19.34)	(1.19)	(4.06)	(−3.26)	(7.67)
Soft cheeses	2	0.73	−0.92	−0.61	0.92	−0.12
		(4.79)	(−9.57)	(−1.82)	(3.09)	(−0.45)
Specialty cheeses	3	0.11	−0.37	−1.78	−0.49	2.54
		(0.48)	(−3.13)	(−3.08)	(−1.26)	(5.89)
Whey cheeses	4	−0.45	0.20	−0.12	−0.49	0.84
		(−4.14)	(2.58)	(−0.37)	(−1.83)	(4.53)
Expenditure share		0.59	0.06	0.16	0.19	

[a]Estimated t-values are in parentheses.

Table A2. Conditional uncompensated price and expenditure elasticities, 1996–1998 values[a]

Commodity	Number	Price				Expenditure
		1	2	3	4	
Stage 1						
Non-alcoholic beverages	1	−0.20	−0.02	−0.29	0.33	0.17
		(−2.34)	(−0.52)	(−3.89)	(3.93)	(2.54)
Cheeses	2	−0.05	−0.39	−0.20	0.53	0.11
		(−0.51)	(−4.76)	(−2.17)	(5.46)	(1.58)
Other foods	3	−0.05	−0.01	−0.49	−0.15	0.70
		(−5.15)	(−3.10)	(−6.75)	(−2.01)	(12.49)
Other nondurables	4	−0.01	−0.00	−0.07	−0.99	1.07
		(−6.24)	(−3.65)	(−6.44)	(−87.67)	(124.54)
Expenditure share		0.019	0.006	0.129	0.847	
Stage 2a						
Fluid milk	1	−0.31	0.52	0.02	0.06	−0.29
		(−4.67)	(8.83)	(0.69)	(1.88)	(−13.91)
Carbonated soft drinks	2	−0.44	−1.42	−0.16	−0.15	2.16
		(−5.08)	(−16.42)	(−3.15)	(−3.05)	(41.92)
Juices	3	−0.79	−0.26	−0.61	0.04	1.61
		(−5.96)	(−1.66)	(−4.23)	(0.41)	(13.07)
Other cold drinks	4	−0.94	−0.83	−0.05	−0.75	2.57
		(−4.74)	(−3.93)	(−0.32)	(−2.31)	(13.64)
Expenditure share		0.44	0.35	0.13	0.08	
Stage 2b						
Standard cheeses	1	−0.94	0.02	0.30	−0.14	0.76
		(−18.64)	(1.12)	(4.05)	(−3.69)	(8.00)
Soft cheeses	2	0.94	−0.91	−0.72	1.07	−0.37
		(4.85)	(−7.72)	(−1.76)	(2.97)	(−1.09)
Specialty cheeses	3	0.05	−0.29	−1.66	−0.34	2.23
		(0.26)	(−3.09)	(−3.53)	(−1.09)	(6.46)
Whey cheeses	4	−0.58	0.27	−0.15	−0.34	0.80
		(−3.99)	(2.57)	(−0.36)	(−0.98)	(3.27)
Expenditure share		0.60	0.04	0.22	0.14	

[a]Estimated *t*-values are in parentheses.

Table A3. Unconditional uncompensated price and expenditure elasticities for beverages calculated at mean values[a]

Commodity	Price							Expenditure
	Fluid milk	Carbonated soft drinks	Juices	Other cold drinks	Cheeses	Other foods	Other nondurables	
Fluid milk	−0.14	0.20	−0.02	−0.01	0.00	0.03	−0.04	−0.03
	(−2.24)	(3.10)	(−0.58)	(−0.22)	(0.41)	(2.83)	(−2.79)	(−2.84)
Carbonated soft drinks	0.35	−0.90	0.06	−0.05	−0.04	−0.64	0.71	0.51
	(3.01)	(−4.45)	(0.66)	(−0.71)	(−0.45)	(−3.16)	(3.52)	(3.25)
Juices	−0.09	0.13	−0.52	0.13	−0.03	−0.41	0.45	0.33
	(−0.60)	(0.67)	(−3.57)	(1.10)	(−0.43)	(−2.78)	(3.16)	(2.96)
Other cold drinks	−0.07	−0.26	0.28	−0.65	−0.05	−0.79	0.89	0.64
	(−0.24)	(−0.71)	(1.11)	(−1.35)	(−0.45)	(−3.14)	(3.14)	(3.01)

[a] Estimated t-values from 100 bootstrap repetitions are in parentheses.

Table A4. Unconditional uncompensated price and expenditure elasticities for cheese calculated at mean values[a]

Commodity	Price							Expenditure
	Standard cheeses	Soft cheeses	Specialty cheeses	Whey cheeses	Beverages	Other foods	Other nondurables	
Standard cheeses	−0.64	0.07	0.31	−0.03	−0.04	−0.14	0.38	0.08
	(−15.32)	(4.38)	(4.06)	(−0.86)	(−0.40)	(−1.64)	(4.05)	(1.52)
Soft cheeses	0.73	−0.94	−0.67	0.91	−0.01	0.02	−0.03	−0.01
	(4.46)	(−8.06)	(−1.61)	(2.53)	(−0.36)	(0.32)	(−0.16)	(−0.30)
Specialty cheeses	1.19	−0.25	−1.86	−0.11	−0.12	−0.52	1.35	0.31
	(3.98)	(−1.57)	(−2.50)	(−0.21)	(−0.35)	(−1.48)	(5.06)	(1.44)
Whey cheeses	−0.09	0.25	−0.08	−0.42	−0.05	−0.17	0.46	0.10
	(−0.87)	(2.53)	(−0.21)	(−1.22)	(−0.41)	(−1.37)	(2.87)	(1.37)

[a]Estimated t-values from 100 bootstrap repetitions are in parentheses.

Essay 4

**Public Policies and the Demand for Carbonated Soft Drinks:
A Censored Quantile Regression Approach**

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Abstract: Heavy consumption of carbonated soft drinks may contribute to obesity, strokes, and cardiac problems. From a health perspective, the distribution of the consumption is at least as important as the mean. Censored as well as ordinary quantile regression techniques were used to estimate the demand for sugary soda based on household data from 1989 to 1999. It was found that heavy drinkers are more price- and expenditure-responsive than are light drinkers. The study shows that increasing the taxes on carbonated soft drinks will lead to a small reduction in consumption for small and moderate consumers and a huge reduction for heavy consumers.

Keywords: carbonated soft drinks, censored quantile regression, demand, taxes

JEL classification: D12, I10, Q11

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Public Policies and the Demand for Carbonated Soft Drinks:
A Censored Quantile Regression Approach

Heavy consumption of carbonated soft drinks may lead to excessive energy intake, contributing to obesity, strokes, and cardiac problems. These problems are increasing in the western world. In addition, soda consumption may contribute to dental caries and diabetes. The Norwegian per capita consumption of carbonated soft drinks is the third highest in the world. However, many Norwegians do not consume soda, indicating that a portion of the population consumes a larger quantity than recommended by health experts. Health experts recommend that no more than 10 percent of the energy intake should come from sugar, which corresponds to an amount of 35 to 40 grams for a child below six years, 45 to 55 grams for a schoolchild, 50 to 60 grams for an adult female, and about 70 grams for an adult male. In comparison, a 0.5 liter bottle of sugary soda normally contains about 50 grams of sugar. Although the mean soda consumption is of interest to producers in order to compute the total demand, it conveys less information to a nutrition expert. To examine the problem from a health perspective, it is important to take account of the whole distribution of the consumption. This is because there may be a greater pay-off from reducing the soda consumption of a heavy consumer than there is in the case of a low or moderate consumer. A person with heavy soda consumption will exceed the intake limit recommended by the experts, and is therefore more exposed to health problems.

This research has three main objectives. First, we will explore the purchase of soda in the whole conditional distribution, and find the factors that influence the demand. The mean effects estimated by limited dependent variable models may be satisfactory if the parameters are identical in the whole distribution. However, the effects are likely to be different for low-consumption households at the lower tail compared to persons with high consumption at the upper tail. Hence, we use a censored quantile regression approach. Second, we will examine whether price changes, which may be induced by tax changes or European Union (EU) membership, have different effects on low, moderate, and heavy soda consumers. Finally, we will model the demand for a censored good without relying on normality and identically distributed errors, two assumptions seldom fulfilled. The demand for censored goods is usually modeled with limited dependent variable models, but the consistency of these models is highly dependent on the normality and homoscedasticity of the error terms.

The next section introduces the empirical model. Then, the quantile regression and censored quantile regression techniques are presented. Next, the data are presented and the results from the quantile regressions are compared with the results from the symmetrically censored least squares (SCLS) model and the Tobit model. Finally, the price elasticities are used to calculate the effects of three different policy scenarios.

The Empirical Model

As the purchase of sugary soda is censored, modeling the demand may best be done within a single equation context. Furthermore, using censored quantile regression, we cannot estimate a demand system with restrictions across the equations. Consequently, we specify Stone's logarithmic demand function. For a discussion, see Deaton and Muellbauer (1980: 60-64). This function may be written as:

$$\ln q^h = \alpha + E\left[\ln x^h - \sum_{j=1}^{n} w_{jt} \ln p_{jt}\right] + \sum_{j=1}^{n} e_j^* \ln p_{jt} \tag{1}$$

where q^h is household h's per capita consumption of soda, x^h is total per capita expenditure on non-durables, w_{jt} is the average expenditure share on good j in the survey period t, and p_{jt} is the nominal price. The expenditure elasticity, E, the compensated price elasticity, e_j^*, and α are the parameters to be estimated. Homogeneity in prices and total expenditure requires that $\sum_j e_j^* = 0$. Consequently, we may impose homogeneity by deflating the price variables in the term $\sum_j e_j^* \ln p_{jt}$ with one of the prices. The expression $\sum_{j=1}^{n} w_{jt} \ln p_{jt}$ is Stone's price index. Moschini (1995) showed that this index is not invariant to changes in the units of measurement. To avoid this potentially serious problem, we used the (log of) CPI[1], which is a Laspeyres index and therefore invariant to changes in units of measurement (Moschini, 1995).

The constant term in equation (1) is expanded to include non-economic variables. A^h is the age of the head[2] of household h, T_t is the two-week mean temperature in period t, CH is a dummy variable for Christmas, and SC is a dummy variable taking account of the differences in demand before and after the introduction of the 0.5 liter plastic bottle with screw cap. Furthermore, the socioeconomic dummy and seasonal variables, Z^h, defined in table 2, and a stochastic error term, ε^h, are included. The model includes prices for two commodities only: sugary soda, and all other non-durables. Since expenditure on soda constitutes a marginal share of expenditures on non-durables, the prices for non-durables except for soda and the CPI are approximately equal. Consequently, homogeneity is imposed by deflating the soda price with the CPI. Then, the model to estimate becomes:

$$(2) \ln q^h = \alpha_0 + \alpha_1 \ln A^h + \alpha_2 \ln T_t + \alpha_3 CH_t + \alpha_4 SC_t + \sum_{k=1}^{K} \beta_k Z_k^h + E \ln \frac{x^h}{CPI_t} + e^* \ln \frac{p_t}{CPI_t} + \varepsilon^h.$$

The compensated price elasticity, e^*, is approximately equal to the uncompensated price elasticity, because soda purchases constitute a very small share of the total consumption.

Quantile Regression and Censored Quantile Regression

Both quantile regression and censored quantile regression are used in labor economics, but have rarely been used to study food consumption. Some exceptions are Manning (1995), who studied the demand for alcohol using quantile regression, and Variyam et al. (2002) and Variyam (2003), who study demand for nutrition using quantile regression. Steward et al.

(2003) used censored quantile regression to study the effect of an income change on fruit and vegetable consumption in low-income households.

As discussed by Deaton (1997), quantile regression is most useful when the errors are heteroscedastic. Heteroscedasticity is frequently present in household expenditure data, meaning that the set of slope parameters of the quantile regressions will differ from each other as well as from the Ordinary Least Squares (OLS) parameters.

We say that a person consumes a product at the θ^{th} quantile of a population if he or she consumes more of the product than the proportion θ of the population does and less than the proportion (1-θ) consumes. Thus, half the households in a sample consume more than the median and half consume less. Similarly, 75 percent of the households consume less than the 0.75 quantile and 25 percent consume more. The unconditional quantile function is defined as the inverse of the cumulative distribution function.

Conditional quantile functions, or quantile regressions, define the conditional distribution of a dependent variable as a function of independent variables. If we have a relation as follows:

(3) $$y_i = x_i'\beta + \varepsilon_i$$

where x_i is a vector of covariates and ε_i is a stochastic error term, the conditional expectation is $E(y_i \mid x_i) = x_i'\beta$, provided that $E(\varepsilon_i|x_i) = 0$. Likewise, the conditional quantile function $Q_\theta(y_i|x_i) = x_i'\beta(\theta)$ if the θ^{th} quantile of ε_i is zero. However, the coefficient vector β depends on the quantile θ. Quantile regression, as introduced by Koenker and Basset (1978), is the solution to the following minimization problem:

(4) $$\min_{\beta} \frac{1}{N} \left\{ \sum_{y_i \geq x_i'\beta} \theta | y_i - x_i'\beta | + \sum_{y_i < x_i'\beta} (1-\theta) | y_i - x_i'\beta | \right\}.$$

Given equation (4), no explicit expression exist for the estimators. Koenker and Basset (1978) showed that under some rather general conditions a unique solution of (4) exists. The minimization problem can be solved by linear programming (LP) techniques for the different quantiles of y. These methods are described in Koenker and D'Orey (1987) and Portnoy and Koenker (1997). When $\theta = 0.5$, the problem is minimizing the absolute value of the residuals, which is a median regression. By estimating different quantile regressions, it is possible to explore the entire shape of the conditional distribution of y, not just the mean, as in linear regressions. This implies that we can explicitly model the price and income reactions at different points in the conditional distribution of the demand function.

Quantile estimators are robust estimators, and are less influenced by outliers in the dependent variables than the least squares regression. When the error term is non-normal, quantile regression estimators may be more efficient than least squares estimators (Buchinsky, 1998). If the error terms are heteroscedastic, and the heteroscedasticity depends on the regressors, the estimated coefficients will have different values in the different quantile regressions. Potentially different solutions at distinct quantiles may be interpreted as differences in the response of the dependent variable to changes in the covariates at various points in the conditional distribution of the dependent variable. Quantile regressions are, like the OLS method, invariant to linear transformations.

Koenker and Basset (1982) introduced a formula for calculating the covariance matrix of the estimated parameters. However, in the Stata manual (StataCorp, 2001) it is argued that bootstrap methods give better estimates for the covariance matrix.

For a given set of prices, purchasing a product is partly a matter of income and partly a matter of taste. Zero observations are not necessarily the result of high prices or low incomes. When data is censored from below at zero, limited dependent variable models are often used. These models are dependent upon assumptions of normality and homoscedasticity in the error terms. Failure to fulfill these assumptions leads to inconsistent estimates of the parameters. Hurd (1979), Nelson (1981), and Arabmazar and Schmidt (1981) showed that estimating limited dependent variables with heteroscedasticity in the error terms leads to inconsistent parameter estimates. Goldberger (1983) and Arabmazar and Schmidt (1982) showed inconsistency because of non-normality in the error terms.

Powell (1984, 1986a) established that, under some weak regularity conditions, the censored quantile regression estimators are consistent and asymptotically normal, and that consistency of the estimators is independent of the distribution of the error terms. The only assumption is that the conditional quantile of the error term is zero: $Q_\theta(\varepsilon_i|x_i'\beta) = 0$.

One of the most useful properties of quantiles is that they are preserved under monotone transformations. For example, if we have a set of positive observations, and we take logarithms, the median of the logarithm will be the logarithm of the median of the untransformed data. The censored regression model, where purchase is censored from below at zero, can be written as:

(5) $$y_i = \max\left\{0, x_i'\beta + \varepsilon_i\right\}.$$

Because of the properties of the quantile function, the conditional quantile of this expression may be written as:

(6) $$Q_\theta(y_i \mid x_i) = \max\left\{0, Q_\theta(x_i'\beta + \varepsilon_i \mid x_i)\right\} = \max(0, x_i'\beta)$$

when the conditional quantile of the error term is zero. Powell (1986a) shows that β can be consistently estimated by:

(7) $$\min_\beta \frac{1}{N}\sum_{i=1}^{n} \rho_\theta\left[y_i - \max\left\{0, x_i'\beta\right\}\right]$$

where $\rho_\theta(\lambda) = \left[\theta - I(\lambda < 0)\lambda\right]$. I is an indicator function which is equal to 1 when the expression is fulfilled and zero otherwise. For observations where $x_i'\beta \le 0$, max $(0, x_i'\beta) = 0$

and ρ is not a function of β. Hence, (7) is minimized using only those observations for which $x_i'\beta > 0$. Based on this fact, Buchinsky (1994) suggested an iterative LP algorithm in which the first quantile regression is run on all the observations, and the predicted values of $x_i'\beta$ are calculated. These calculations are used to discard sample observations with negative predicted values. The quantile regression is then repeated on the truncated sample. The parameter estimates are used to recalculate $x_i'\beta$ for the new sample, the negative values are discarded, and so on, until convergence. We have used this algorithm in combination with the qreg procedure in Stata.

The model estimated by quantile regression and censored quantile regression was compared with the model estimated by the SCLS method and the Tobit method. The SCLS estimation method proposed by Powell (1986b) is based on the "symmetric trimming" idea. If the true dependent variable is censored at zero and symmetrically distributed around $x'\beta$, we observe the dependent variable as asymmetrically distributed due to the censoring. However, symmetry can be restored by "symmetrically censoring" at $2\,x'\beta$. This is done below with the algorithm proposed in Johnston and DiNardo (1997). First, we estimate β using OLS on the original data. Then, we compute the predicted values. If the predicted value is negative, we set the observation to missing. If the predicted value of the dependent value is greater than twice the predicted value, we set the value of the dependent variable equal to $2\,x_i'\beta$. We then run OLS on these altered data. Finally, we repeat this procedure until convergence is achieved. The t-values were found by 100 bootstrap repetitions.

The Tobit model has the following likelihood function:

$$L = \prod_{y_i=0}\left[1-\Phi\left(\frac{x_i'\beta}{\sigma}\right)\right].\prod_{y_i>0}\frac{1}{\sqrt{2\pi\sigma^2}}\exp\left[-\frac{1}{2}\frac{(y_i-x_i'\beta)^2}{\sigma^2}\right],$$

where y is the left-side variable and x is the vector of right-side variables. To obtain estimates of the marginal effects that are comparable to the SCLS parameters, we have to multiply the parameter estimates with the probability of a positive outcome: $\beta^{*} = \beta \Pr(y_i > 0)$. We use the share with positive consumption, which is a consistent estimate of the probability.

Data

The sample is obtained from the household expenditure surveys of Statistic Norway over the period from 1989 to 1999. Each year, between 1200 and 1400 households kept account of their purchases over a two-week period. Thus, our total sample consists of about 14,000 observations. The households are evenly distributed throughout the year and throughout the country, so the data are representative. The surveys were conducted continuously, with new households participating every year, so our data consist of repeated cross-section samples. For food products, the quantities purchased and the corresponding expenditures are recorded. Table 1 shows the yearly per capita consumption of sugary carbonated soft drinks from 1989 to 1999. The years are in the first column. In the second column, the percentage of the sample with zero observations each year is presented. Then, the quantiles 0.25, 0.50, 0.75, 0.90, and 0.95 follow. The quantiles presented in the table are asymmetric to emphasize the high-consumption households. The mean values for each year follow the quantiles, and “Dis” is the yearly mean value of the disappearance data from the Breweries’ Association. We note that the mean value of the disappearance data is between 62 to 92 percent higher than the mean value in the survey data. One likely explanation for this difference is that many children do not report the whole quantity of soda purchase to their parents (who keep the accounts), and many adults forget to report the soda they buy at the gas station and similar places. “% Sug” is the share of the total carbonated soft drink sales that contain sugar.

The last row shows statistics from linear regressions, using year as the explanatory variable in each regression and the other columns as dependent variables. Trend is the parameter value, which measures the expected change in liters purchased from one year to another. We note that the share of the households that do not purchase sugary carbonated soft drinks is decreasing. The purchased quantity is increasing in all the quantiles, but the biggest increase is at the upper tail. All the trend parameters are significantly different from zero at the five percent level.

Table 1 about here

While the expenditures are derived directly from the surveys, we used price variables derived from the consumer price index (CPI). Although we could have constructed unit prices, these would reflect quality as well as price variations. In addition, unit prices are missing for households that do not purchase any sugary soda. Because of these problems, we used the soda price sub index from the CPI as an explanatory variable. The CPI is a monthly[3] Laspeyres index, where the sub indexes have fixed weights that are changed once a year according to the observed changes in budget shares.

To take account of the climatic conditions in Norway, with long winters and short summers, we introduce a temperature variable. We assume that when the temperature is above 15 degrees Celsius, people do more outdoor activities like sports, hiking, bathing, picnicking, and so on, thereby increasing the demand for soda. The temperature variable is constructed as the two-week mean temperature measured at the meteorological stations located in each of the six regions of Norway that are included in this study. These variables are linked to the households according to purchase time and place of abode. Further, we assume that temperatures below 15 degrees Celsius do not influence soda consumption. Therefore, the temperature variable has a value of one below 15 degrees Celsius, whereas above 15 degrees Celsius it has the value of the temperature.

Table 2 shows the variables in categories corresponding to the quantile groups defined by the purchase of carbonated soft drinks. The quantile groups are defined according to the distribution of the dependent variable, measured by an index of per capita sugary soda expenditures divided by the soda price index. The "Zero" column shows the mean values for the households that did not purchase sugary soda in the survey period. The following five columns show the mean values for the quantile groups, and the last column gives the mean values of all the households. The 0.25 quantile group reports the mean values for the 25 percent of households with the lowest per capita sugary soda purchases, including the households in the "Zero" column. The 0.50 quantile group shows the mean values of the households having between 25 and 50 percent of the lowest sugary soda consumption, and so on. The "1" column shows the mean values for the 10 percent of households with the highest per capita consumption of sugary soda.

The first row in table 2 consists of the mean values of the dependent variable[4] in each quantile group. The next row shows the expenditure variable, which is the logarithm of the expenditure per capita deflated by the CPI. The third row lists the average soda price deflated with the CPI. The age of the head in each household and the temperature variable follow. The next variable is a Christmas dummy variable to account for the Christmas period. This variable has a value of one in the 26th two-week period and zero otherwise. In addition, we include a dummy variable to take account of the introduction of the 0.5 liter bottle with screw cap. Before 1992, soda was sold in small glass bottles containing just 0.33 liters of soda, with an iron cap. Thus, the likelihood of an open bottle being carried around was limited. This likelihood greatly increased after the introduction of the screw cap bottle. To model the combined effects of increased bottle size and the screw cap, we use a dummy variable taking a value of zero before 1992 and a value of one in 1992 and after. Finally, several dummy variables taking care of the household-specific characteristics, location, and time period are introduced.

Table 2 about here

We note that the expenditure variable is higher in the upper part of the distribution than at the mean. Next, the age of household heads declines gradually from the lower to the higher parts of the distribution. In addition, there are more households in the upper 10 percent during Christmas time, and there are fewer households consuming no sugary soda after the introduction of the new screw cap bottle than there were before. Further, one-person households are over-represented in the upper quantile groups, whereas couples with children are over-represented in the middle quantile groups.

Results

Model (2) was estimated using Buchinsky's (1994) algorithm for censored quantile regression, implemented in Stata (StataCorp, 2001). From a health perspective, consumption of soda with sugar is of strong interest. The purchase of soda with sugar represents between 82 and 91 percent of the total soda purchase[5]. Table 3 shows the estimated parameters/marginal effects in five different quantile regressions, and the corresponding marginal effects of the SCLS and the Tobit models. In the 0.25-quantile regression, 26 percent of the observations were censored away. In the 0.5-, 0.75-, 0.90-, and 0.95-quantile regressions, the censoring did not have any effect, and the complete data sample was used. Consequently, we estimated the model simultaneously for these quantiles to take account of the possible correlation between the error terms. The marginal effects of the SCLS and the Tobit models are presented in the two rightmost columns.

The expenditure elasticity is significantly different from zero in all the quantiles, and it increases from 0.25 in the 0.25 quantile to 0.45 in the 0.95 quantile. The price elasticity is not significant in the lowest quantile, whereas at the median it is significant at the 10 percent level, and in all the other quantiles it is significant at the five percent level. The numerical value increases steadily from –0.62 in the 0.25 quantile to –1.60 in the 0.95 quantile. Age has a negative and significant effect in all the quantiles. Except for the lowest quantile, the effect is similar in all the quantiles. The temperature elasticity is about 0.06 in all the quantiles. This means that an increase in the two-week mean temperature from 18 to 19 degrees, which is an increase of 5.6 percent, will increase the demand for soda by 0.34 percent. Further, we can see that the introduction of new and larger bottles with screw caps increased consumption by between 8 and 11 percent. The consumption of carbonated sugary soft drinks shifts upward by about 30 percent in the two-week period around Christmas. Families with children is the reference household, the Central East region is the reference location, and winter is the reference quarter. R^2 is low, which is common when cross-sectional data is used. In the last row, the number of observations for each quantile regression is printed.

We note that the comparable elasticities of the SCLS model are quite near the median in most cases, whereas the Tobit estimates are lower. In some cases, they are even lower than in the 0.25-quantile regression, indicating that the Tobit model is too restrictive.

Table 3 about here

Figure 1 presents the estimates for some of the most important of the quantile elasticities and the corresponding SCLS elasticities. For the expenditure elasticity, the price elasticity, and the age elasticity, we plot the different quantile regression results for 0.25, 0.50, 0.75, 0.90, and 0.95, with the solid curves representing the 90 percent confidence band. The dashed lines represent the SCLS estimates with the 90 percent confidence band. In all the panels, the quantile regression estimates lie at some points outside the confidence interval for the SCLS model, suggesting that the effects of these covariates are not constant across the conditional distribution of the dependent variable.

Figure 1 about here

Results from statistical tests for equality of coefficients across the estimated quantiles are presented in table 4. When one or both the quantile regressions are censored, different parts of the sample are used for estimation, and we cannot obtain the covariance between the regressions. In these cases, we calculate quasi *t*-statistics to test for equality between the coefficients. The quasi *t*-statistics ignore any covariance between the coefficients. The first three columns of table 4 give the quasi *t*-statistics for equality tests of the coefficients at the 0.25 quantile, with the coefficients at the 0.75, 0.90, and 0.95 quantiles. If the numerical value of the *t*-statistics is larger than 1.96, then equality is rejected at the five percent level of significance. As discussed above, censoring was not a problem at the 0.50, 0.75, 0.90, and 0.95 quantiles. Therefore, these equations were estimated simultaneously, and the covariance matrix between the coefficients was calculated by bootstrapping. In the last three columns of table 4, the *t*-statistics of tests for equality between coefficients at the 0.50, 0.75, 0.90, and 0.95 quantiles are reported.

Table 4 about here

The tests reject the H_0 hypothesis of equality for all the expenditure elasticities. For the price elasticities, however, the H_0 hypotheses are not rejected between any of the quantiles. Further, the tests suggest that the age elasticity is less in the 0.25 quantile than in the other quantiles. For the temperature, the tests suggest that the effect is similar in all parts of the distribution. This is also true for the effect of the introduction of larger bottles with screw caps, and for the effect of Christmas. The differences of single households (relative to couples with children) vary across the distribution. The same is true for couples without children and other households as compared with the reference group.

These tests indicate that the effects of many of the covariates are different in different parts of the conditional distribution of soda consumption. Hence, a quantile regression approach is warranted.

The Effects of Public Policies

The demand for carbonated soft drinks containing sugar may continue to increase if nothing is done to prevent it. Unless younger people completely change their attitudes as they age, the negative age elasticity indicates that consumption will increase. The positive expenditure elasticity, together with the steadily growing real household income, will also contribute to growing consumption.

Public authorities have several options for influencing the demand for soda. First, they could ban the sale of soft drinks in schools. Furthermore, they could restrict school children from going outside the school area during school time. Second, as with smoking and drinking, information about the health aspects of soda consumption may be used to prevent further increases in consumption. Last, but not least, economic means may be used to reduce the demand for sugary drinks, either by influencing the income of the households and/or the prices of the products. The disadvantage of influencing household income, for example by income taxes, is that it will have an effect on the consumption of all goods, healthy or unhealthy. Hence, it is better to use prices to influence the consumption.

In Norway, carbonated soft drinks are exposed to a production tax of NOK[6] 1.55 per liter. In addition, soft drinks have a value added tax (VAT) of 12 percent, which is the same as for other food products. Most non-food products have a 24 percent VAT. We will study three price scenarios for sugary carbonated soft drinks. In the first scenario, we use the elasticities from the quantile regression model and the SCLS model to calculate the effects of a doubling of the VAT. This means a price increase of 10.8 percent. In the second scenario, we calculate the impact of doubling the production tax as well as doubling the VAT. This corresponds to a price increase of 27.3 percent. In the third scenario, we study the effect of Swedish prices in Norway. According to Statistics Norway and Eurostat, the European purchase parity survey (Bruksås et al., 2001) shows that Swedish soda and juice prices are about 29.8 percent lower than Norwegian prices. However, the general price level is about 10.4 percent lower, and, correspondingly, the real soda price level is about 21.7 percent lower in Sweden than in Norway. We assume that Norwegian soda prices decrease down to the Swedish level, which may occur if Norway joins the EU. Table 5 shows the results from the three price scenarios in percentages and liters. Purchases in 1999 are used as a base level to calculate the changes in liters.

Table 5 shows that the percentage effects are largest in the upper quantiles. Furthermore, the changes in liters are even larger in the upper quantiles. If the objective is to reduce consumption among the heavy soda consumers, price changes seem to be an effective tool. A doubling of production tax and the VAT will reduce the consumption of the top five percent of soda consumers by approximately 44 percent, or 74 liters per year. The lowest soda consumers will reduce their consumption by 17 percent, or about two liters per year. The mean effects are calculated using the SCLS elasticities. They are between the median and the 0.75 quantile in all the scenarios, which is reasonable. To find the effects of a price change on the zero-consumption households, we estimated a binary logit model. The own-price parameter was very small and insignificant. Hence, we believe that price changes will not have any effect on the zero-consumption households.

Table 5 about here

Concluding Remarks

Our analysis investigates the demand for sugary carbonated soft drinks and how the authorities may influence consumption. Steady increases in consumption of soft drinks have been observed for many years. Until recently, studies have focused on average values, but because heavy consumption of sugary soft drinks contributes to obesity and other health issues, the focus should be on heavy consumption. Moderate or low consumption is of less concern.

The results show that many of the covariates have different effects in different parts of the conditional distribution, warranting a quantile regression approach. Heavy drinkers are more expenditure-responsive than light drinkers are, whereas age seems to be more important at and above the median than below it. While the expenditure effect is positive, the age effect is negative. This means that the trend towards increasing consumption of sugary soda will continue if young people do not drastically change their habits when they grow older. Steady growth in incomes and the consumption trend will almost surely continue, pushing soda consumption higher, with the highest growth in the upper quantiles.

High temperature increases consumption, and has a similar effect on sugary soda consumption in all the quantiles. Due to the change in the bottle type, from the 0.33 liter glass bottle with an iron cap to the 0.5 liter plastic bottle with a screw cap, the demand shifted upwards by about 10 percent in all quantiles.

The study shows that a doubling of the production tax and the value added tax will reduce the consumption of sugary soda by two liters per year for the moderate consumers and by 74 liters per year for those in the top five percent in terms of consumption.

Notes

1. Our version of the CPI does not include durables.
2. The head of the household is defined as the person who contributes most to the family economy.
3. One problem with combining the survey data with the monthly price indices is that the survey period may involve two different months. We solved this problem in the following way. For the households keeping accounts within one month, we used the prices for that month. For the households keeping accounts in a period overlapping two months, we used a weighted average of the prices for the two months, using the number of days in the survey period in each month as weights.
4. The dependent variable is in logarithmic form, after adding one to avoid ln(0). However, here it is shown untransformed.
5. We attempted to estimate a model involving all carbonated soft drinks – those with sugar and those with artificial sweetener. However, it turned out that the demand for soda with artificial sweetener was not very responsive to price. In addition, we obtained very unclear estimates for both total soda consumption and consumption of soda with artificial sweetener.
6. The exchange rate from the Central Bank of Norway is currently US$1 = 6.96 NOK (January 19, 2004).

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Table 1. Distribution of Annual per Capita Purchases of Sugary Carbonated Soft Drinks

Year	Zero%	Quantile					Mean	Dis	%Sug
		0.25	0.5	0.75	0.9	0.95			
1989	33	0	17	52	96	121	34		89
1990	35	0	16	49	87	124	33		83
1991	33	0	20	52	104	143	38		83
1992	24	1	26	62	100	135	41	73	82
1993	25	1	27	59	107	143	43	77	82
1994	21	7	33	72	121	156	49	95	85
1995	21	17	29	68	120	169	49	95	86
1996	20	9	39	75	126	181	54	96	86
1997	18	10	39	78	124	171	56	106	89
1998	19	8	36	74	117	163	51	101	89
1999	16	12	39	78	130	169	57	106	91
Trend (in liters)	–1.9	1.4	2.5	3.1	3.8	5.4	2.5	4.6	1.3

Note: The quantities are measured in liters per capita per year.
Dis = the mean value from the disappearance data.
% Sug = the percentage of sugary soda purchases in the total soda purchase.

Table 2. Average Values of Variables in Different Quantile Groups

Variable	Zero	Quantile Group					Mean
		0.25	0.50	0.75	0.90	1.0	
Indexes							
Soda consumption	0.0	0.0	0.7	1.9	3.6	7.4	1.9
Total expenditure	5.4	5.4	5.3	5.4	5.5	5.7	5.4
Price of soda	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Age (Year)	52.4	52.4	44.1	43.5	42.4	42.2	45.6
Temperature	2.0	2.0	2.1	2.4	2.7	2.8	2.3
Dummy variables in %							
Christmas	2.6	2.7	2.0	3.0	4.4	6.4	3.2
Screw cap	63.4	64.1	76.8	77.6	78.0	75.4	73.9
Household type							
One person	31.0	30.3	5.8	7.7	9.5	17.9	14.2
Couple without children	32.9	33.0	18.6	17.6	17.7	23.5	22.3
Couple with children	22.1	22.6	59.2	59.2	56.8	43.1	48.1
Single parent	3.5	3.6	5.2	4.8	4.7	4.9	4.6
Other household	10.4	10.5	11.2	10.7	11.5	10.5	10.9
Region							
Central East	20.5	20.6	20.4	18.2	18.0	20.2	19.5
Other East	26.6	26.4	26.1	27.5	30.7	31.1	27.7
South	14.4	14.6	14.7	15.0	13.7	12.6	14.4
West	17.7	17.7	18.2	19.1	18.0	16.8	18.1
Central	9.4	9.2	10.2	9.3	9.8	9.6	9.6
North	11.4	11.4	10.4	10.9	9.8	9.7	10.6
Season							
Winter	26.6	26.4	25.3	23.6	22.8	18.7	24.1
Spring	25.8	25.8	26.1	28.3	27.6	30.5	27.2
Summer	19.8	19.8	21.7	21.8	23.2	23.7	21.7
Fall	27.8	28.0	27.0	26.3	26.4	27.0	27.0

Table 3. Quantile Regression, SCLS and Tobit Estimates

Variable	Quantile					SCLS	Tobit
	0.25	0.50	0.75	0.90	0.95		
Total expenditure	0.25	0.31	0.38	0.43	0.45	0.31	0.27
	(13.17)	(17.60)	(23.47)	(22.25)	(16.36)	(25.83)	(24.44)
Price of soda	–0.62	–0.77	–1.05	–1.48	–1.60	–0.88	–0.55
	(–1.39)	(–1.93)	(–2.47)	(–3.21)	(–2.20)	(–2.59)	(–1.89)
Age	–0.16	–0.37	–0.38	–0.35	–0.32	–0.35	–0.33
	(–4.80)	(–11.47)	(–12.14)	(– 9.00)	(–7.49)	(–11.67)	(–18.39)
Temperature	0.06	0.07	0.06	0.06	0.06	0.06	0.05
	(5.02)	(6.62)	(6.86)	(4.92)	(2.97)	(6.00)	(6.44)
Screw cap	0.11	0.11	0.10	0.10	0.08	0.11	0.10
	(3.80)	(4.27)	(3.36)	(3.22)	(1.67)	(5.50)	(5.26)
Christmas	0.28	0.32	0.31	0.30	0.33	0.28	0.23
	(6.01)	(5.57)	(5.84)	(6.05)	(5.02)	(7.00)	(7.25)
One person	–0.83	–0.61	–0.31	–0.04	0.09	–0.59	–0.47
	(–13.62)	(–20.55)	(–8.38)	(–0.90)	(1.88)	(–19.67)	(–25.33)
Couple without	–0.56	–0.30	–0.14	–0.03	–0.01	–0.28	–0.24
children	(–19.29)	(–12.76)	(–6.11)	(–1.28)	(–0.38)	(–14.00)	(–16.00)
Single parent	–0.14	–0.16	–0.06	–0.04	–0.01	–0.14	–0.12
	(–4.04)	(–4.65)	(–1.32)	(–0.90)	(–0.10)	(–4.67)	(–4.86)
Other household	–0.23	–0.06	0.02	0.05	0.06	–0.05	–0.05
	(–8.66)	(–2.05)	(0.73)	(1.64)	(1.62)	(–2.50)	(–2.68)
Other East	0.18	0.17	0.15	0.12	0.12	0.16	0.12
	(6.76)	(6.75)	(6.30)	(4.42)	(3.17)	(8.00)	(7.52)
South	0.06	0.06	0.04	0.02	0.06	0.05	0.03
	(2.11)	(1.94)	(1.29)	(0.67)	(1.26)	(2.50)	(1.49)
West	0.15	0.10	0.08	0.03	0.00	0.10	0.07
	(5.43)	(3.98)	(3.44)	(1.11)	(0.07)	(5.00)	(4.16)
Central	0.16	0.12	0.11	0.08	0.02	0.13	0.09
	(4.80)	(3.77)	(3.25)	(2.77)	(0.32)	(5.21)	(4.17)
North	0.13	0.09	0.05	0.02	0.05	0.09	0.05
	(3.94)	(3.10)	(1.61)	(0.50)	(0.90)	(3.58)	(2.32)
Spring	0.07	0.08	0.10	0.11	0.10	0.08	0.07
	(2.96)	(3.69)	(4.71)	(4.21)	(3.04)	(4.71)	(4.51)
Summer	0.04	0.01	0.03	0.06	0.05	0.03	0.03
	(1.52)	(0.63)	(1.28)	(2.26)	(1.21)	(1.29)	(1.55)
Fall	–0.03	–0.02	–0.01	0.01	–0.03	–0.02	–0.02
	(–1.01)	(–0.64)	(–0.51)	(0.27)	(–0.85)	(1.20)	(–0.97)
Constant	–0.50	0.41	0.51	0.48	0.54	0.36	0.31
	(–3.21)	(2.61)	(3.53)	(2.60)	(2.48)	(2.93)	(3.21)
R^2	0.03	0.08	0.06	0.07	0.08	0.21	0.06
# observations	10282	13985	13985	13985	13985	13985	13985

Note: The *t*-values are reported in parentheses.

Table 4. Tests for Equality of Coefficients across Quantiles

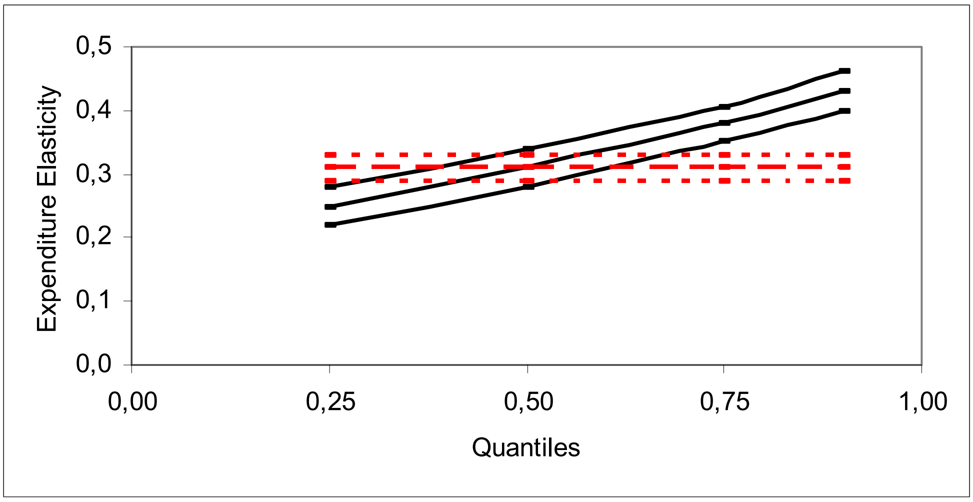
	$q_{25} = q_{75}$	$q_{25} = q_{90}$	$q_{25} = q_{95}$	$q_{50} = q_{90}$	$q_{50} = q_{95}$	$q_{75} = q_{95}$
Total Expenditure	–5.15*	–7.00*	–6.45*	5.80*	4.47*	2.29*
Price of soda	0.68	1.28	1.24	1.44	1.17	0.82
Age	5.09*	4.17*	2.86*	0.37	1.17	1.68
Temperature	–0.09	–0.13	0.14	0.37	0.49	0.22
Screw cap	0.26	0.24	0.68	0.24	0.67	0.56
Christmas	–0.45	–0.24	–0.64	0.32	0.24	0.36
One person	–7.86*	–11.67*	–12.50*	12.90*	12.92*	8.36*
Couple without children	–11.27*	–13.34*	–11.68*	8.74*	9.28*	4.99*
Single parent	–1.60	–1.91	–2.00*	2.72*	2.22*	0.86
Other household	–6.41*	–6.85*	–5.82*	3.06*	2.88*	1.27
Other East	0.68	1.38	1.14	1.47	1.11	0.69
South	0.65	0.96	0.13	0.91	0.00	0.44
West	1.84	2.92*	3.08*	2.03*	2.35*	2.13*
Central	1.16	1.74	2.51*	1.03	1.73	1.78
North	1.76	2.36*	1.48	2.05*	0.76	0.10
Spring	–0.85	–1.27	–0.75	1.16	0.50	0.10
Summer	0.31	–0.48	–0.17	1.62	0.84	0.50
Fall	–0.40	–0.89	0.06	0.79	0.35	0.51
Constant	–4.79*	–4.41*	–3.84*	0.36	0.51	0.14

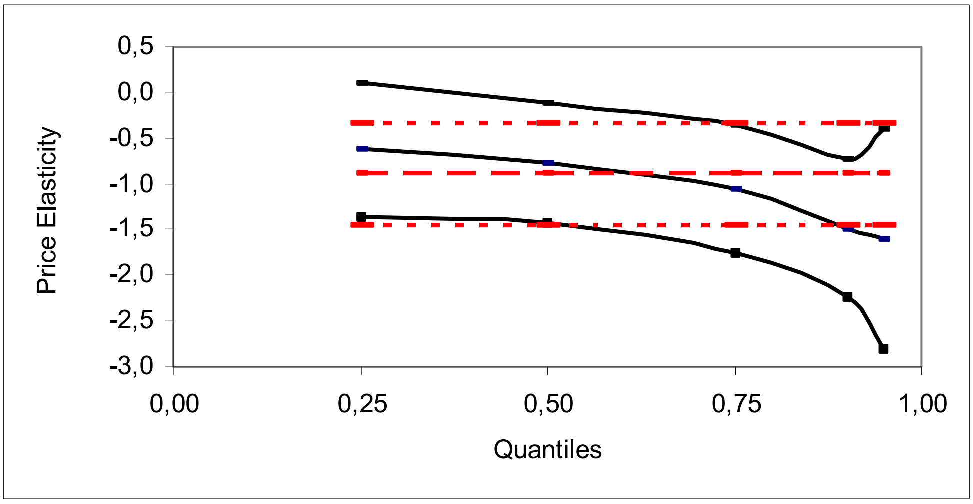
Note: An asterix indicates significance at the five percent level.

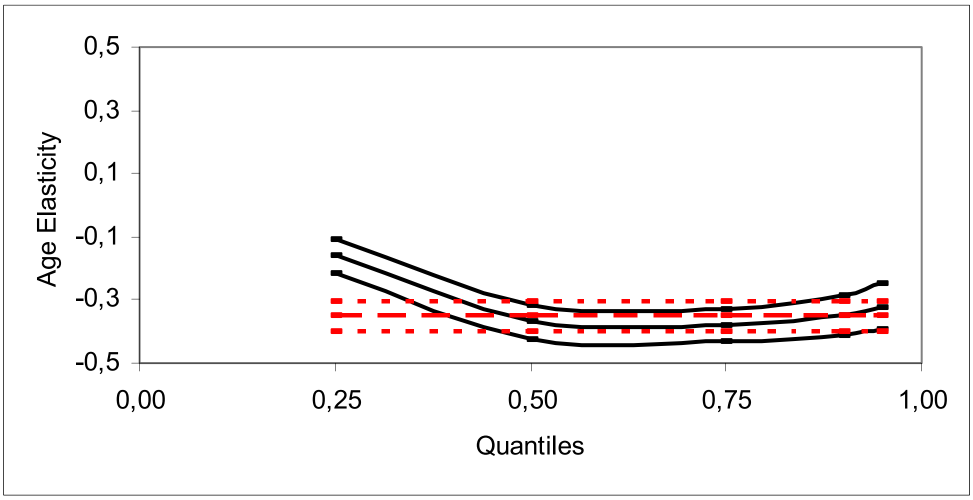
Table 5. Predicted Annual Changes in Soda Purchases per Capita due to Price Changes

Policy Change	Quantile					
	0.25	0.50	0.75	0.90	0.95	SCLS
Doubling of VAT for soda						
Change in percent	–6.7	–8.3	–11.3	–16.0	–17.3	–9.5
Change in liters	–0.8	–3.2	–8.8	–20.8	–29.2	–5.1
Doubling of VAT and production tax for soda						
Change in percent	–16.9	–21.0	–28.7	–40.0	–43.7	–24.0
Change in liters	–2.0	–8.2	–22.4	–52.5	–73.8	–12.9
Swedish prices in Norway						
Change in percent	13.5	16.7	22.8	32.1	34.7	19.1
Change in liters	1.6	6.5	17.8	41.8	58.7	10.2

Figure 1. Quantile Regression SCLS Estimates with 90 Percent Confidence Intervals







Essay 5

A Censored Quantile Regression Analysis of Vegetable Demand: Effects of Changes in Prices, Income, and Information

by

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Abstract: Low consumption of vegetables is linked to many diseases. From a health perspective, the distribution of consumption is at least as important as mean consumption. We investigated the differential effects of policy changes on high- and low-consuming households by using 15,700 observations from 1986 to 1997. Many households did not purchase vegetables during the two-week survey periods and censored as well as ordinary quantile regressions were estimated. Removal of the value added tax for vegetables, income increases, and health information are unlikely to substantially increase purchases in low-consuming households. Nevertheless, information provision is cheap and best targeted at low-consuming households.

Keywords: censoring, consumption, public policies, quantile regression, vegetables.

JEL classification: D12, I10, Q11

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A Censored Quantile Regression Analysis of Vegetable Demand: Effects of Changes in Prices, Income, and Information

Many diseases, including cardiovascular diseases, certain types of cancer, obesity, and diabetes, are linked to dietary behavior. According to the World Health Organization (2002), diet-related diseases account for more than three million premature deaths in Europe each year. One of the six leading diet-related risk factors is low intake of fruit and vegetables, and nutrition experts recommend that the consumption of fruit and vegetables should at least be doubled in Northern Europe (Elinder, 2003).

Because the risks of dietary inadequacies and adverse health effects are most serious in households consuming low quantities of vegetables, the distribution of consumption across households is at least as important as the mean consumption. We used 15,700 observations of household purchases over the 1986–1997 period. Table 1 shows the average percentages of households reporting zero purchase of vegetables in each two-week survey period, the mean annual per capita purchases in kilograms calculated from the sample, and the reported distribution of the purchases[1]. When a household purchases at the θ^{th} quantile of the purchase distribution, it purchases less than the proportion θ of the households and more than the proportion $(1 - \theta)$. Thus, at the 0.75-quantile, 75% of the households purchase less (or equal) and 25% purchase more than the specified household. The numbers in the 0.50-quantile column show the median purchases. In 1997, 6% of the households did not purchase any vegetables during the survey period, the annual purchase at the 0.10-quantile was 5 kilograms, the median purchase was 30 kilograms, the mean purchase was 35 kilograms, and the purchase at the 0.90-quantile was 75 kilograms. Clearly, from a public health perspective, investigating households at the lower tail of the consumption distribution is of greater importance than studying those around the mean.

Information about the linkages between diseases and dietary behavior is likely to influence the consumption of different foods in the households. Following Brown and Schrader (1990), we use a health-information index based on the number of articles dealing with the linkages between fats, heart diseases, and the diet. We expect that an increasing number of such articles will decrease the consumption of several types of meats and fats and increase the consumption of vegetables. We will investigate the effects on vegetable consumption of a 10% increase in information as measured by the index.

Nutrition experts (e.g., French, 2003) claim that more than just information campaigns are needed to increase the consumption of vegetables and have proposed price subsidization. Such subsidization could, for example, be the removal of the VAT on vegetables. Rickertsen, Chalfant, and Steen (1995) found that Norwegian own-price elasticities for different vegetables ranged from –0.30 to –0.85, which suggests that per capita vegetable demand is responsive to such price changes. We will investigate the effects of removing the current VAT of 12% on the purchase of vegetables.

Income changes may increase the consumption of vegetables as discussed in, for example, Stewart, Blisard, and Jolliffe (2003). They used censored quantile regression (CQR) methods to investigate to what extent poor US households increased their expenditure on fruit and vegetables following an income increase. They concluded that poor households are unresponsive to income changes. We will investigate whether a 10% increase in income, measured as total expenditures on nondurables and services, would cause low-consuming households to increase their consumption of vegetables.

Six percent to 10% of the households reported zero purchases of vegetables during the survey period and our data set is censored. Tobit models are typically used to correct for censoring and we estimate the conditional mean effects of changes in the independent variables by using a Tobit model. However, the effects are likely to be different for low-consuming households and a Tobit model may provide rather poor estimates for these households. Furthermore, a Tobit model does not give consistent estimates if the error term is heteroscedastic or non-normally distributed. Censoring is mainly a problem for households at the lower quantiles of vegetable purchases and we use a CQR for these quantiles. For high-consuming households, censoring is not a problem and ordinary quantile regressions (QR) are used. QR as well as CQR provide consistent estimates when the error terms are heteroscedastic or non-normally distributed. Applications of QR to food demand include Variyam, Blaylock, and Smallwood (2002) who found that the risk of dietary inadequacy is greater at the lower tail of the US nutrient intake distribution than at the mean, and Variyam (2003) who found that education has a stronger effect at the upper tail of the intake distribution in the US.

Table 1 about here

Empirical Model

We use Stone's logarithmic demand function as discussed in, for example, Deaton and Muellbauer (1980:60–4)

$$(2) \qquad \ln q^h = \alpha + E\left[\ln x^h - \sum_{j=1}^{n} w_{jt} \ln p_{jt}\right] + \sum_{j=1}^{n} e_j^* \ln p_{jt} \,,$$

where q^h is household's h consumption of vegetables, x^h is total expenditure on nondurables and services, w_{jt} is the average expenditure share on good j in survey period t, and p_{jt} is the corresponding price. The expenditure elasticity for vegetables, E, the compensated price elasticities, e_j^*, and α are parameters. Homogeneity in prices and total expenditures requires that $\sum_j e_j^* = 0$ and we impose homogeneity by deflating the prices with the price of nondurables and services. The price index in equation (1) is Stone's price index and Moschini (1995) showed that this index varies with the units of measurement. To avoid this potentially serious problem, we use a Laspeyres index as suggested by Moschini.

The constant term in equation (1) is expanded to include health-related information, $\ln I_t$, the age of the head[2] of the household, $\ln A^h$, socio-economic dummy variables, Z_k^h, quarterly dummy variables, D_{st}, and a stochastic error term, ε^h, such that

(3) $$\alpha = \alpha_0 + \alpha_1 \ln I_t + \alpha_2 \ln A^h + \sum_{k=1}^{K} \beta_k Z_k^h + \sum_{s=1}^{S} \gamma_s D_{st} + \varepsilon^h .$$

Quantile Regression and Censored Quantile Regression

A linear regression model defines the conditional mean of the dependent variable, y, as a linear function of the vector of explanatory variables, x, or

(4) $$y_i = x_i'\beta + \varepsilon_i \text{ and } E(y_i \mid x_i') = x_i'\beta ,$$

where ε is an error term. Correspondingly, QR defines the conditional quantiles of the dependent variable as a function of the explanatory variables. QR enables us to describe the entire conditional distribution of the dependent variable given the explanatory variables. In our case, the changes in purchases of vegetables in low- and high-consuming households caused by changes in prices, health information, and other variables are estimated.

The QR model, as introduced by Koenker and Basset (1978), can be written as

(5) $$y_i = x_i'\beta_\theta + \varepsilon_{\theta i} \quad \text{and} \quad Q_\theta(y_i \mid x_i) = x_i'\beta_\theta ,$$

where $Q_\theta(y_i \mid x_i)$ denotes the θ^{th} conditional quantile of y_i. The QR estimator of β_θ is found by solving the problem

(6) $$\min_{\beta_\theta} \frac{1}{N} \left\{ \sum_{y_i \geq x_i'\beta_\theta} \theta \mid y_i - x_i'\beta_\theta \mid \; + \sum_{y_i < x_i'\beta_\theta} (1-\theta) \mid y_i - x_i'\beta_\theta \mid \right\}.$$

This minimization problem can be solved by linear programming for the different quantiles of the dependent variable as described in, for example, Koenker and D'Orey (1987) or Portnoy and Koenker (1997). In the case where $\theta = 0.5$, the problem is reduced to minimizing the sum of the absolute deviations of the error terms, which results in the least absolute deviation (LAD) estimator.

Heteroscedasticity is frequently a problem associated with cross-sectional data and QR is most potent in the presence of heteroscedasticity (Deaton, 1997). If the heteroscedasticity depends on the regressors, the estimated slope parameters will be different in the different quantiles. However, when the distribution of the errors is homoscedastic, the estimated slope parameters of QR and ordinary least squares (OLS) are identical and only the intercepts differ (Deaton, 1997: 80). When the distribution of the errors is symmetrical, the intercepts are also identical. Two other characteristics of the QR model are worth noting (Buchinsky, 1998). First, when the error terms are not normally distributed, the QR estimator may be more efficient than the OLS estimator. Second, the QR parameter estimates are relatively robust to outliers because the objective function depends on the absolute value of the residuals and not, as in OLS, the square of the residuals.

Many low-consuming households did not purchase vegetables during the survey period and so the data are censored at zero. A standard procedure to correct for zero censoring is to use a Tobit model as discussed in, for example, Amemiya (1984). The Tobit model can be written as

$$(7) \qquad y_i = \begin{cases} x_i'\beta + \varepsilon_i & \text{if } x_i'\beta + \varepsilon_i > 0 \\ 0 & \text{if } x_i'\beta + \varepsilon_i \leq 0. \end{cases}$$

However, if the error term is not normally distributed and homoscedastic, the estimated coefficients of the Tobit model are biased and inconsistent. Powell (1986) showed that, under some weak regularity conditions, the censored quantile regression estimators are consistent independently of the distribution of the error term and, furthermore, asymptotically normal. The CQR model with purchases censored at zero, can be written as

$$(8)\qquad Q_\theta(y_i \mid x_i) = \max\left\{0, Q_\theta(x_i'\beta_\theta + \varepsilon_{\theta i} \mid x_i)\right\} = \max(0, x_i'\beta_\theta)$$

when the conditional quantile of the error term is zero. The CQR estimator of β_θ is found by solving

$$(9)\qquad \min_{\beta_\theta} \frac{1}{N}\sum_{i=1}^{N} \rho_\theta\left[y_i - \max\left\{0, x_i'\beta_\theta\right\}\right],$$

where $\rho_\theta(\lambda) = [\theta - I(\lambda < 0)\lambda]$ and I is an indicator function taking the value of 1 when the expression holds and zero otherwise. For observations where $x_i'\beta \leq 0$, max $(0, x_i'\beta) = 0$ and (8) is minimized by using only the observations where $x_i'\beta > 0$. Therefore, Buchinsky (1994) suggested the iterative algorithm that we have used in combination with the qreg procedure in Stata. This algorithm starts by using all the observations to calculate the predicted values, $x_i'\beta_\theta$. Next, observations associated with negative predicted values are deleted and the model is reestimated on the trimmed sample. This procedure is repeated until convergence of two succeeding iterations is achieved. In the case where $\theta = 0.5$, the CQR estimator is identical to the censored least absolute deviation (CLAD) estimator. The standard errors of the parameter estimates are obtained by the bootstrapping procedure described in StataCorp (2001).

Data

The data were obtained from the household expenditure surveys of Statistic Norway over the 1986–1997 period. Each year, a nationally representative sample of about 1400 households was recruited; the total sample consists of about 15,700 cross-sectional observations. For food products, the quantities of different food items purchased and the corresponding expenditures were recorded. Since calculated unit prices may reflect quality as well as price differences and, furthermore, unit prices are missing for households not purchasing vegetables in the survey period, the consumer price index (CPI) for each good is used. The CPI is a monthly Laspeyres index with fixed weights within the year but changing weights over the years according to the observed changes in expenditure shares[3].

As discussed above, many diseases are linked to dietary behavior, and information about these linkages is likely to influence the consumption of different foods in the households. Following Brown and Schrader (1990), we include a health-information index based on the number of articles published in the Medline database. Our index is based on articles dealing with the linkages between fats, heart diseases, and the diet and is described in more detail in Rickertsen, Kristofersson, and Lothe (2003). Contrary to Brown and Schrader (1990), it is assumed that information has a limited life span and there is no cumulative effect. We use a two-week version of the index and assume that the effects of information accumulate over six two-week periods and have zero effect after that period.

Table 2 shows the distribution of the dependent and the explanatory variables. The quantile groups are defined according to the distribution of vegetable purchases measured by an index of per capita vegetable expenditures divided by the vegetable price index. The "Zero" column shows the mean values for the households not purchasing vegetables in the survey period. The following five columns show the mean values for the quantile groups and the last column gives the mean values for all the households. The 0.10-quantile column reports the mean values for the 10% with the lowest vegetable purchases including the households in the "Zero" column, the 0.25-quantile column shows the mean values for the households having between the 10% and 25% lowest vegetable purchases, and so on.

The first row gives the mean values of the dependent variable. There is a wide distribution in the purchases of vegetables. The next rows show indexes of the total expenditures on nondurables and services, the price variables, and the health information index. There is not much variation in these variables across the quantiles. Next, dummy variables defining regions, degree of urbanization, season, and household type are reported. The dummy variables are reported as percentages of the total. The three largest cities of Norway are defined as major cities. The reference household lives in the “Central East region”, in an “urban area”, is surveyed during “winter”, and comprises a “couple with children”. Note that households in the Central East region, in the major cities, and comprising couples without children are strongly represented in the 0.90-quantile, which indicates that many of these household types purchase large quantities of vegetables. On the other hand, relatively few households in rural areas and comprising couples with children are represented in the 0.90-quantile. There is a high representation of households in rural areas and one-person households in the 0.10-quantile, whereas households in non-major cities and comprising couples with or without children are underrepresented. Finally, the age of the head of the household is reported. Other potentially important personal characteristics, such as education or ethnic origin, were not recorded in the surveys.

Table 2 about here

Results

Equations (1) and (2) were estimated and table 3 shows the estimated coefficients of the quantile regressions and the marginal effects of the Tobit model. The marginal effects are the maximum likelihood coefficient estimates multiplied by the estimated probability of a positive purchase and they are included for comparison. In the 0.10- and 0.25-quantiles, 17.8% and 0.7% of the households were deleted because of the censoring algorithm. In the 0.50-, 0.75-, and 0.90-quantiles, censoring did not affect the coefficient estimates and these quantiles were estimated simultaneously by ordinary QR. When simultaneous estimation is used, we can use the covariance matrix to test for equality of the parameters in the different quantiles. The *t*-values for the quantile regression estimates were found by bootstrap resampling with 100 replications.

The price coefficients reported in table 3 are the compensated elasticities. The uncompensated price elasticities are calculated by the Slutsky equation and they are presented in table 4. Except for the cross-price elasticity between vegetables and non-food items, the values of the compensated and uncompensated price elasticities do not differ greatly. The own-price elasticity changes from around –0.2 in the lower quantiles to around –0.4 in the higher quantiles, which suggests that high-consuming households are more responsive to price changes than are low-consuming households. In the 0.50-, 0.75-, and 0.90-quantiles, the own-price elasticity is significantly different from zero at the 5% level. The cross-price elasticity between vegetables and meats (including fish) is negative and significantly different from zero except in the 0.90-quantile. The complementary relationship is especially strong in low-consuming households. This complementarity is not surprising given that vegetables are frequently consumed with meat or fish as part of a hot meal. The cross-price elasticities between vegetables and other foods and vegetables and non-food items are not significant. The price elasticities calculated by the Tobit model are quite different from the elasticities for households in the 0.10- and 0.25-quantiles.

The expenditure elasticity is highly significant and increases slightly from about 0.3 in the 0.10-quantile to about 0.4 in the 0.90-quantile, which suggests that increases in income will result in increased purchases of vegetables. However, the effect is strongest in high-consuming households.

The effect of health-information is declining when moving from the lowest to the highest quantile, which illustrates the usefulness of quantile regressions. In the 0.10-quantile, the effect of a 1% increase in health information is a 0.11% increase in the purchases of vegetables and this effect is significantly different from zero. In the high-consuming households, the effect of health information is not significantly different from zero, which suggests that the effect of information occurs mainly in low-consuming households. In the Tobit model, the health-information effect is not significantly different from zero.

The reference region is East and the purchases in the other regions are lower in all the quantiles. The purchases in the three major cities are higher and the purchases in rural areas are lower than the purchases in urban areas. The lower purchases in rural areas may, at least to some extent, be explained by a limited selection of fresh vegetables in these areas. As expected, the purchases in the spring and summer are higher than in the winter.

The effects of the household composition variables are quite different in the different quantiles. The reference household comprises a couple with children. The effect of moving to a one-person household is –0.87 in the 0.10-quantile and 0.25 in the 0.90-quantile. The negative effect as well as the positive effect are highly significant. There are also significant negative effects for low-consuming couples without children and significant positive effects for high-consuming couples without children. Finally, age has a significantly positive effect on vegetable purchases and the effect is higher in low- than in high-consuming households. The R^2 values are low but in line with previous studies (e.g., Variyam, Blaylock, and Smallwood, 2002).

Table 3 about here

Table 4 about here

Figure 1 summarizes the quantile and Tobit coefficient estimates of the key policy variables: own price, total expenditure, and health information. The dashed lines in each figure show the Tobit estimates with conventional 90% confidence intervals. The solid lines show the quantile estimates with 90% point wise confidence intervals. In all the panels, the quantile regression estimates lie at some point outside the confidence intervals of the Tobit model, which suggests that the effects of the policy variables are not constant across the conditional distribution of vegetable purchases. The same is true for many of the other independent variables.

Results of statistical tests for equality of coefficients across the estimated quantiles are presented in table 5. When one or both of the quantile regressions are censored, different parts of the sample are used for estimation and we cannot obtain the covariance between the regressions. By ignoring any covariance between the coefficients, quasi *t*-statistics can be calculated to test for equality of the coefficients across the quantiles. The first five columns of table 5 give the quasi *t*-statistics for equality of the coefficients at the 0.10- and 0.25-quantiles with the coefficients at the 0.50-, 0.75-, and 0.90-quantiles. If the numerical value of the *t*-statistics is larger than 1.96, then equality is rejected at the 5% level of significance. As discussed above, censoring was not a problem at the 0.50-, 0.75- and 0.90-quantiles. Therefore, these equations were estimated simultaneously and the covariance matrix between the coefficients was calculated by bootstrapping. In the last column of table 5, the *t*-statistics of tests for equality of the coefficients at the 0.50- and 0.90-quantiles are reported.

The test results show that the effects of many of the independent variables are significantly different in different parts of the conditional distribution of vegetable purchases, which further demonstrates the usefulness of the quantile regression approach. Equal effect of a change in total expenditure is rejected when testing the quantile estimates at $q_{10} = q_{90}$ and also at the $q_{10} = q_{75}$ as well as at the $q_{50} = q_{90}$. However, the differences are quite small and interestingly the expenditure elasticity is highest in high-consuming households. Equal effect of a change in health information is rejected at the $q_{10} = q_{90}$ as well as at the $q_{10} = q_{75}$, which suggests that health information is more efficient at increasing the purchases in low- than in high-consuming households. On the other hand, the differences in the reported own-price elasticities are not statistically significant at the 5% level. Equality of the household composition coefficients is rejected in most cases whereas equality for the regional dummy coefficients is usually not rejected.

Figure 1 about here

Table 5 about here

Vegetable Purchases and Public Policies

The effects of three policy options on vegetable purchases are evaluated. The effects of removing the current VAT of 12%, increasing income approximated by total expenditures by 10%, and increasing health information by 10% are investigated.

If any of these policy options were pursued, some non-purchasing households could start purchasing vegetables. However, a binary logit model including the explanatory variables described in table 2 predicted only minor changes in the number of non-purchasing households and we assumed that the number remained constant in the policy analysis.

Table 6 shows the predicted changes in per capita vegetable purchases from the quantile regressions and the Tobit model. The percentage changes and the changes in kilograms are calculated using 1997 as the base year. From a health perspective, changes in the physical quantities are of most interest.

Several results are important. First, none of the proposed policies is really successful in substantially increasing purchases, measured in physical quantities, by low-consuming households.

Second, VAT removal is not well targeted at low-consuming households. The percentage change in purchases caused by VAT removal is almost twice as high in the 0.75- or 0.90-quantile as in the 0.10-quantile. Furthermore, the change in kilograms is more than 20 times as high, which demonstrates that VAT removal would mainly increase the purchases in high-consuming households and suggests that the health benefits would be relatively small compared with the costs. Furthermore, the annual cost associated with removing the VAT for vegetables is about $170 millions[4]. We note that the effects predicted by the Tobit model are close to the median effects of the quantile model but quite different from the effects at the lower quantiles.

Third, income increases are very costly compared with VAT removal and not well targeted at increasing the vegetable purchases in low-consuming households. The effects of a 10% increase in total expenditure are relatively constant across households, varying from a 3.20% increase for low-consuming to a 3.90% increase for high-consuming households. However, households in the 0.10 quantile will increase their purchases by only 0.16 kilograms whereas households in the 0.90 quantile will increase their purchases by 2.93 kilograms.

Fourth, the increases in vegetable purchases caused by increases in health information are not large. A 10% increase in information increases the purchases of vegetables from 0.06 to 0.12 kilograms per capita in the lower quantiles. In the higher quantiles, there are no effects of information, which suggests that information has a stronger relative effect as well as absolute effect in low- than in high-consuming households. Moreover, information is relatively cheap compared with VAT removal or income increases, and it is possible to target information campaigns at low-consuming households.

Table 6 about here

Conclusions and Policy Implications

Low consumption of vegetables is linked to many diseases. From a health perspective, the distribution of consumption across households is more important than the mean consumption, and the consumption in low-consuming households is of special interest. Our results clearly suggest that the marginal effects of policy-relevant variables are different in different parts of the conditional distribution of vegetable purchases, which demonstrates the usefulness of a quantile regression approach.

Different public policies can be pursued to increase vegetable purchases. The removal of the VAT will mainly increase the purchases by high-consuming households and the health benefits may be relatively low. The estimated total expenditure elasticity for vegetables increases from around 0.3 in low-consuming households to around 0.4 in high-consuming households. Consequently, income support is not a well-targeted policy instrument to increase the vegetable purchases in low-consuming households. Furthermore, income support is costly. Health information has a significant and positive effect on vegetable purchases in low-consuming households whereas there is no significant effect in high-consuming households. Our results suggest that none of the proposed policies would be very successful at substantially increasing the purchases of vegetables in low-consuming households. However, price and income policies are very costly and, furthermore, not well targeted at low-consuming households. Providing more information seems to be a better targeted and much cheaper policy option.

Notes

1. Vegetables produced by the household or received as a gift are included in table 1. Vegetables consumed away from home or vegetables included in industrially prepared foods, which are not classified as vegetables, are excluded.
2. The head of the household is defined as the household member with the highest income.
3. For households having a survey period including two months, we used a weighted average of the CPI for those two months. The number of survey days in each month was used as weights.
4. The exchange rate was $1 = NOK 6.96 (January 19, 2004).

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Table 1. Distribution of Annual per Capita Vegetable Purchases

Year	Zero%	Quantile					Mean
		0.10	0.25	0.50	0.75	0.90	
1986	8	3	11	25	46	75	35
1987	8	3	12	26	45	72	35
1988	9	2	11	26	49	77	35
1989	10	1	12	27	50	79	38
1990	9	2	11	26	47	74	37
1991	10	1	13	27	49	82	39
1992	6	4	13	26	46	72	35
1993	6	4	13	28	49	79	37
1994	6	5	15	29	48	74	37
1995	7	5	14	28	50	75	36
1996	6	5	15	30	51	78	38
1997	6	5	15	30	51	75	35

Table 2. Mean Values of the Variables in Different Quantile Groups

Variable	Zero	Quantile					Mean
		0.10	0.25	0.50	0.75	0.90	
Indexes							
Vegetable consumption	0.0	0.1	0.8	1.8	3.2	5.2	3.1
Total expenditure	5.4	5.3	5.2	5.3	5.4	5.6	5.4
Price of vegetables	189.6	190.0	190.0	190.8	191.8	191.2	190.9
Price of meats	220.3	220.3	219.6	219.7	220.2	220.0	220.0
Price of other foods	242.8	244.1	243.8	245.7	247.6	247.1	246.1
Price of non-food items	235.6	237.1	236.9	238.9	241.1	240.5	239.4
Health information	26.6	26.4	26.3	26.7	26.6	26.2	26.4
Dummy variables in %							
Region							
Central East	19.7	17.8	12.5	15.5	20.8	25.8	20.0
Rest of East	28.9	27.8	28.3	28.8	27.7	27.4	27.8
South	11.4	13.2	15.7	14.8	13.7	11.8	13.7
West	16.1	17.4	20.3	18.8	17.5	17.1	17.8
Central	11.9	11.8	11.8	10.8	9.6	7.8	9.8
North	12.1	11.9	11.3	11.2	10.8	10.0	10.9
Urbanization							
Major city	18.3	16.6	12.9	14.1	18.5	22.6	17.9
Non-major city	54.7	55.3	60.9	61.7	62.7	61.5	60.7
Rural area	26.9	28.2	26.3	24.3	18.8	15.9	21.4
Season							
Winter	23.4	23.7	24.1	24.0	22.8	20.5	22.7
Spring	27.3	26.6	25.5	26.9	28.2	30.1	27.8
Summer	20.8	20.9	21.0	20.3	22.8	23.7	21.9
Fall	28.6	28.8	29.4	28.8	26.2	25.6	27.6
Household type							
One person	47.0	36.8	9.1	10.4	11.3	15.6	15.5
Couple without children	17.1	15.9	17.2	18.1	22.8	29.6	22.9
Couple with children	21.3	31.5	55.2	55.2	49.5	39.1	45.5
Single parent	6.1	6.3	5.9	4.4	4.0	3.2	4.3
Other household	8.6	9.6	12.5	11.9	12.3	12.5	11.8
Age (years)	45.5	45.1	44.7	45.2	46.5	48.6	46.5

Table 3. Quantile Regression and Tobit Estimates

Variable	Quantile					Tobit
	0.10	0.25	0.50	0.75	0.90	
Total expenditure	0.32	0.36	0.36	0.38	0.39	0.33
	(13.00)	(21.63)	(25.52)	(39.42)	(26.78)	(34.22)
Price of vegetables	–0.21	–0.23	–0.38	–0.41	–0.37	–0.31
	(–1.24)	(–1.77)	(–4.53)	(–4.21)	(–3.38)	(–3.88)
Price of meats	–0.39	–0.50	–0.29	–0.17	–0.18	–0.24
	(–2.62)	(–4.43)	(–3.96)	(–3.13)	(–1.75)	(–3.49)
Price of other foods	–0.41	0.42	0.12	0.08	0.11	0.08
	(–0.49)	(0.67)	(0.25)	(0.20)	(0.19)	(0.21)
Price of non-food items	1.00	0.31	0.55	0.50	0.44	0.47
	(1.51)	(0.61)	(1.32)	(1.43)	(0.98)	(1.50)
Health information	0.11	0.06	0.04	–0.01	–0.01	0.03
	(2.54)	(1.94)	(1.62)	(–0.58)	(–0.56)	(1.53)
Rest of East	–0.03	–0.07	–0.06	–0.09	–0.09	–0.06
	(–0.94)	(–2.60)	(–3.35)	(–4.76)	(–6.20)	(–4.21)
South	–0.13	–0.12	–0.12	–0.14	–0.12	–0.11
	(–3.29)	(–3.99)	(–5.15)	(–5.68)	(–5.67)	(–6.10)
West	–0.06	–0.09	–0.09	–0.13	–0.14	–0.09
	(–1.75)	(–3.52)	(–4.22)	(–6.05)	(–7.75)	(–5.61)
Central	–0.18	–0.18	–0.19	–0.21	–0.22	–0.18
	(–4.22)	(–5.90)	(–10.88)	(–11.88)	(–9.98)	(–9.32)
North	–0.07	–0.08	–0.08	–0.10	–0.08	–0.07
	(–1.80)	(–2.70)	(–3.98)	(–3.72)	(–2.71)	(–3.86)
Major city	0.08	0.06	0.06	0.06	0.05	0.06
	(2.30)	(2.61)	(4.36)	(4.23)	(2.64)	(3.52)
Rural area	–0.15	–0.12	–0.09	–0.06	–0.03	–0.08
	(–5.32)	(–5.65)	(–5.64)	(–3.17)	(–1.57)	(–6.40)
Spring	0.07	0.10	0.10	0.07	0.07	0.08
	(2.05)	(3.94)	(5.42)	(3.89)	(3.11)	(5.08)
Summer	0.10	0.09	0.09	0.05	0.06	0.07
	(2.64)	(3.17)	(4.37)	(3.05)	(2.21)	(4.01)
Fall	0.05	0.01	–0.02	–0.04	–0.03	–0.01
	(1.21)	(0.32)	(–1.05)	(–2.14)	(–1.19)	(–0.62)
One person	–0.87	–0.61	–0.14	0.09	0.25	–0.23
	(– 8.35)	(–23.53)	(–6.07)	(4.29)	(7.89)	(–14.66)
Couple without children	–0.13	0.00	0.10	0.17	0.25	0.06
	(–4.45)	(0.12)	(8.18)	(9.75)	(13.93)	(4.47)
Single parent	–0.38	–0.23	–0.09	–0.03	–0.01	–0.14
	(–6.63)	(–6.05)	(–2.92)	(–0.84)	(–0.26)	(–5.56)
Other household	–0.14	–0.05	0.00	0.04	0.09	–0.02
	(–4.12)	(–1.89)	(0.04)	(2.42)	(4.44)	(–1.21)
Age	0.35	0.34	0.26	0.24	0.18	0.28
	(8.51)	(12.93)	(12.64)	(11.41)	(7.33)	(17.64)
Constant	–3.28	–3.01	–2.25	–1.81	–1.40	–2.26
	(–11.41)	(–15.05)	(–16.71)	(–10.65)	(–9.47)	(–18.63)
R^2	0.06	0.08	0.08	0.11	0.13	0.07
Sample size	12889	15574	15688	15688	15688	15688

Note: The t-values are reported in the parentheses.
The Tobit estimates are the estimated parameters multiplied by the probability of purchasing vegetables.

Table 4. Uncompensated Price Elasticities

Elasticity	Quantile					Tobit
	0.10	0.25	0.50	0.75	0.90	
Price of vegetables	–0.21	–0.23	–0.38	–0.41	–0.38	–0.31
	(–1.24)	(–1.78)	(–4.57)	(–4.27)	(–3.46)	(–3.90)
Price of meats	–0.41	–0.52	–0.31	–0.19	–0.20	–0.26
	(–2.74)	(–4.61)	(–4.22)	(–3.53)	(–1.96)	(–3.75)
Price of other foods	–0.45	0.37	0.07	0.03	0.05	0.04
	(–0.55)	(0.59)	(0.14)	(0.06)	(0.10)	(0.09)
Price of non–food items	0.75	0.02	0.27	0.19	0.13	0.20
	(1.13)	(0.05)	(0.64)	(0.56)	(0.29)	(0.66)

Note: The *t*-values are reported in the parentheses.

Table 5. Tests for Equality of Coefficients across Quantiles

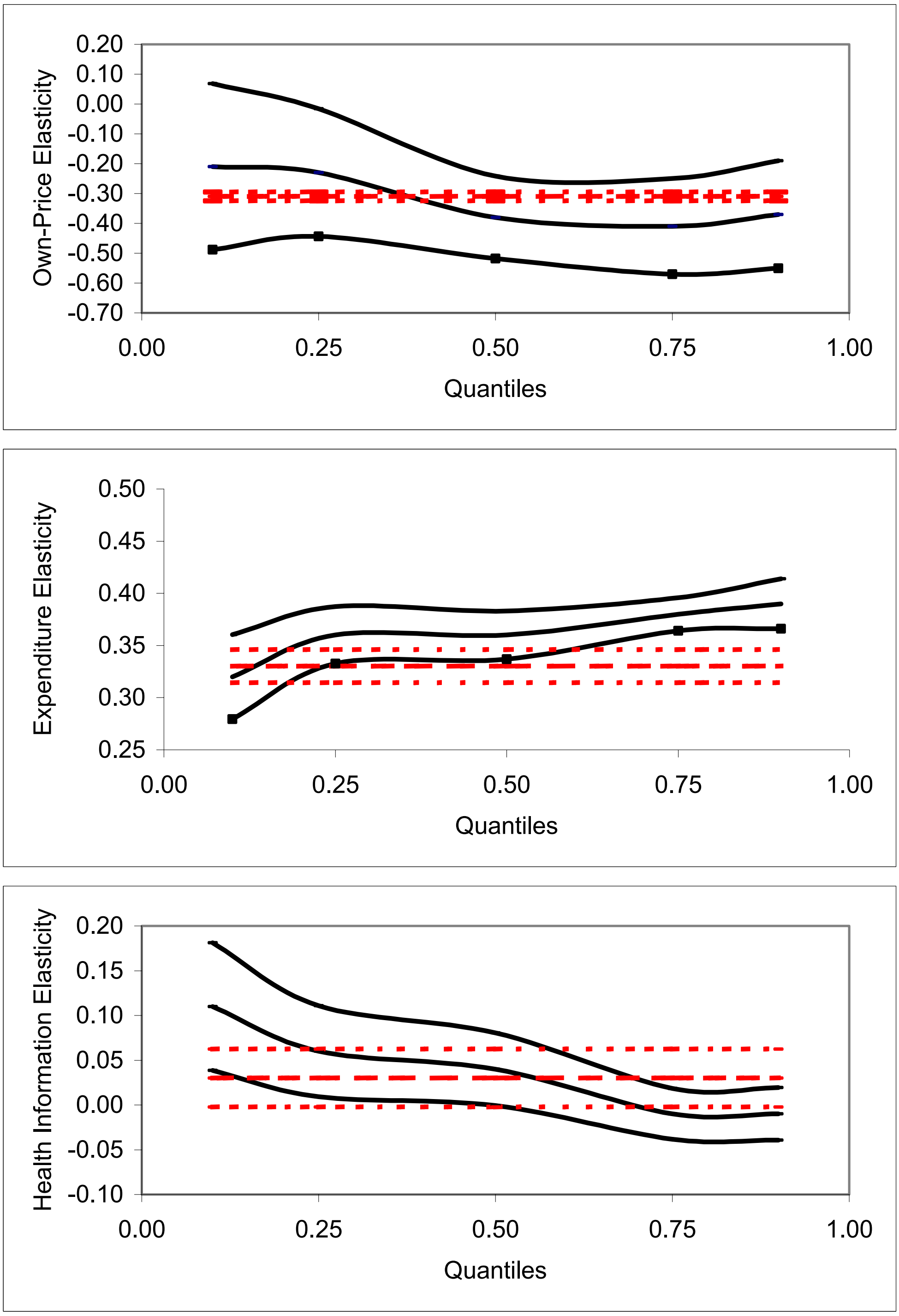
Variable	$q_{10} = q_{90}$	$q_{25} = q_{90}$	$q_{10} = q_{75}$	$q_{25} = q_{75}$	$q_{10} = q_{50}$	$q_{50} = q_{90}$
Total expenditure	–2.70*	–1.67	–2.36*	–1.21	–1.40	2.27*
Price of vegetables	0.83	0.86	1.04	1.13	0.91	0.00
Price of meats	–1.17	–2.12*	–1.28	–2.32*	–0.62	0.96
Price of other foods	0.52	0.37	–0.51	0.43	–0.55	0.00
Health information	2.41*	1.79	2.50*	1.90	1.53	1.59
Rest of East	1.29	0.74	1.19	0.61	0.71	1.39
South	–0.22	–0.06	0.30	0.62	–0.11	0.17
West	1.57	1.26	1.30	0.89	0.54	2.26*
Central	0.67	0.85	0.58	0.72	0.19	1.26
North	0.12	–0.06	0.45	0.37	0.09	0.10
Major city	0.68	0.46	0.47	0.20	0.38	0.59
Rural area	–3.53*	–3.11*	–2.61*	–2.00*	–1.82	2.88*
Spring	–0.02	0.89	–0.08	0.87	–0.67	0.96
Summer	1.04	0.94	1.21	1.15	0.40	0.96
Fall	1.56	0.90	1.84	1.23	1.56	0.14
One person	–7.59*	–23.43*	–6.52*	–19.13*	–4.93*	13.12*
Couple without children	–10.90*	–8.43*	–9.02*	–6.12*	–6.83*	8.61*
Single parent	–5.52*	–4.34*	–5.38*	–4.16*	–4.56*	1.84
Other household	–5.69*	–4.10*	–4.59*	–2.74*	–3.54*	4.18*
Age	3.76*	4.87*	2.60*	3.34*	2.00*	3.33*
Constant	–5.68*	–6.24*	–4.58*	–4.88*	–3.17*	4.99*

Note: An asterisk indicates significance at the 5% level.

Table 6. Predicted Changes in Vegetable Purchases and Changes in Policy Variables

Policy Change	Quantile					Tobit
	0.10	0.25	0.50	0.75	0.90	
Removal of VAT for vegetables						
Change in percent	2.25	2.46	4.07	4.39	4.07	3.32
Change in kilogram	0.11	0.37	1.22	2.24	3.04	1.11
10% increase in expenditures						
Change in percent	3.20	3.60	3.60	3.80	3.90	3.30
Change in kilogram	0.16	0.54	1.08	1.94	2.93	1.16
10% increase in health information						
Change in percent	1.10	0.60	0.40	–0.10	–0.10	0.30
Change in kilogram	0.06	0.09	0.12	–0.05	–0.08	0.11

Figure 1. Quantile Regression and Tobit Estimates with 90% Confidence Intervals



Geir Wæhler Gustavsen

Geir Wæhler Gustavsen was born in Oslo in 1960. He holds a Master in Economics (cand. polit) from the University of Oslo (1993).

The main objective of this thesis is to investigate the demand for food products from the producer and health perspectives. The thesis consists of five essays that explore Norwegian consumers' reactions to changes in prices of food products, and the effects of income, advertising, health information, and food scares. In the first essay, the main conclusion is that information on mad cow disease (BSE) did not change beef consumption in Norway. This result may be explained by the fact that no BSE cases were detected in Norway and, moreover, that consumers trusted the producers and controlling authorities. The second essay investigates the effects of advertising on milk demand. The conclusion is that, although milk advertising has a positive effect on total milk demand, such advertising is not profitable for producers. The third essay explores different methods for making forecasts of demand for food products, specifically dairy products. In the fourth essay, the demand for carbonated soft drinks containing sugar is investigated. From a public health perspective, the demand from high-consuming households is more important than the average demand. The main conclusion in essay four is that an increase in the taxes on carbonated soft drinks will lead to a small reduction in consumption by households with a small or moderate consumption and a huge reduction in households with a large consumption. In the fifth essay, the problem is the opposite. An increase in the demand for vegetables by low-consuming households is more important than an increase in the average demand. It is shown that the removal of the value added tax for vegetables, increases in income, and increases in health information are unlikely to substantially increase vegetable purchases by low-consuming households. Nevertheless, information provision is cheap and may be well targeted at low-consuming households.

Professor Kyrre Rickertsen was the adviser of this dissertation.

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