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Estimating preference change in meat demand in Saudi Arabia

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Abstract

The purpose of this paper is to investigate the preference change in the demand for meat subject to random coefficients in Saudi Arabia. A Fortran 77 program has been designed to estimate the demand function for meat using Kalman filtering techniques and maximum likelihood approach. The initial values of the coefficient and covariance estimates are an essential prior information in the Kalman filtering techniques. Results provide substantial random coefficients in red meat, implying important structural change occurs in red meat more than poultry and fish demand.

1. Introduction

The result of the shock in the Saudi economy in the past two decades caused a change in behavioral consumption among the Saudi population. The nation of Saudi Arabia is becoming more urbanized and cosmopolitan. The level of education has risen very sharply. Medical care has improved. Technology for storing frozen and chilled foodstuffs has increasingly adopted. These factors, along with increased average real income, have improved standard of living and changed significantly the structure and pattern of consumption.

The Saudi economy, over the period study, was facing two stages of economic phenomena: the first stage was the economic boom during late 1970's and early 1980's; and the second stage was the stable economy in late 1980's. The economic variables were changing and affected from one year to the next over the stabilization period. Accordingly, food consumption was affected by this phenomena. Food quality, such as fat and cholesterol level, is the major concern among the Saudi consumers recently. Thus, important shift in meat preferences may have produced. Making available information on expected meat demand will facilitate policy makers to reduce the potential of a meat shortage. All the previous studies made on demand function for meat have used the classical fixed-parameter models which might lead to poor information on projected meat demand. Thus, the objective of this paper is to investigate the preference change in the demand for meat. Appropriate econometric methods subject to ran-

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dom coefficient will help analyzing this change in the demand for meat in Saudi Arabia.

2. Model

Economists usually used classical ordinary least-squares with fixed-parameter over sample observations to estimate demand functions. However, this assumption is too restrictive with changing in preferences in demand functions if there is large variation in income and prices. Random coefficient models are more adequate to study the structural change in demand functions. Econometricians are able to relax the constant coefficient assumption in the linear model to randomly fluctuate across different observations.

The single random coefficient model (Hildreth and Houch, 1968; Swamy and Mehta, 1975; Cooley and Prescott, 1974) has extended to multi-regression model using seemingly unrelated regression approach (Singh and Ullah, 1974). Garbade (1977) and Chavas (1983) have discussed in details the estimation of variable parameter regression. Switching regressions and random coefficients were introduced by Quandt (1972) and Swamy and Mehta (1975). In Meinhold and Singpurwalla (1983), Kalman filter has been used in some non-engineering applications such as short-term forecasting and the analysis of life lengths from dose-response experiments. Abraham and Ledolter (1983) have conveniently described the procedures of implementing the Kalman filtering techniques (see Kalman, 1961). Generalized least-squares (Sant, 1977) and Bayesian estimation (Sarris, 1973) are different approaches can be used to estimate random coefficient regression models and they are equivalent to Kalman filtering techniques (Chavas, 1983).

The linear model most frequently used in statistical applications may be indicated as follows:

$$Y_t = X_t \beta_t + e_t \tag{1}$$

$$e_{ti} \sim N(0, \sigma_i^2) \tag{2}$$

where $Y_t = a(N*1)$ is the vector of observations of N dependent variables, $X_t = a(N*P)$ the matrix of t observations on P independent variables, $\beta_t = a(P*1)$ the vector of coefficients, and $e_t = a(N*1)$ the vector of the disturbance term, normally distributed with zero mean and scalar variance, with $t = 1, 2, \dots, T$ and $i = 1, 2, \dots, N$.

The dynamic evolution of the β_t vector is assumed to follow a random walk with zero drift through time for a specific dependent variable (Garbade, 1977):

$$\beta_t = \beta_{t-1} + u_t \tag{3}$$

$$u_t \sim N(0, \sigma^2 \Omega) \tag{4}$$

where $u_t = a(P*1)$ is a random vector, serially uncorrelated with e_t, and $\Omega =$ a stationary covariance ratio matrix of the innovation u_t. If $\Omega = 0$ (no process noise), Eqs. (1) and (2) become the classical fixed coefficient model. If $\Omega \neq 0$, the parameter vector is random and structural change should be considered. The random coefficients can be estimated by implementing Kalman filter and maximum likelihood approaches. A Kalman filter is a recursive, unbiased least-squares estimator of a Gaussian random signal (Wegman, 1982). Thus, initial estimate of b_0 and Σ_0 must be provided. Random coefficients, β_t, are sequentially estimated under the assumption of b_t is a vector estimate of β_t and Σ_t is the covariance matrix of b_t. The Kalman filter provides the following sequential estimator of β_t in the model of Eqs. (1) and (3) (Chavas, 1983; Sage and Melsa, 1971).

$$b_t = b_t|_{t-1} + G_t(Y_t - X_t' b_t|_{t-1}) \tag{5}$$

where

$$b_t|_{t-1} = b_{t-1} \tag{6}$$

$$G_t = \Sigma_t|_{t-1} X_t (X_t' \Sigma_t|_{t-1} X_t + 1)^{-1} \tag{7}$$

$$\Sigma_t|_{t-1} = \Sigma_{t-1} + \Omega \tag{8}$$

$$\Sigma_t = \Sigma_t|_{t-1} - G_t X_t' \Sigma_t|_{t-1} \tag{9}$$

$$\Omega = K^2 \Sigma_0 \tag{10}$$

$$b_t | Y_{t-1} \sim N(\beta_{t-1}, \sigma^2 \Sigma_t|_{t-1}) \tag{11}$$

$$b_t | Y_t \sim N(\beta_t, \sigma^2 \Sigma_t) \tag{12}$$

in which K^2 is the ratio of the variance of the process noise to the variance of parameter estimates, and G_t the gain filter.

Eqs. (6) and (8) are the prior estimate of β_t and prior covariance of b_t, respectively. The prior estimate $b_t|_{t-1}$ plus the prediction error $(Y_t - X_t'b_t|_{t-1})$ weighted by the gain of the filter G_t produce the posterior estimate of β_t as given in Eq. (5). Eq. (9) simply present the posterior variance Σ_t which is the prior variance $\Sigma t|_{t-1}$ minus the posterior semi-definite matrix $G_t X_t \Sigma_t|_{t-1}$.

In the fixed coefficient model (i.e., $\Omega = 0$), β_t is constant for all t and $\Sigma_t|_{t-1} = \Sigma_{t-1}$. Thus, b_t and Σ_t are equal to their ordinary least-squares analogues (Sage and Melsa, 1971). The scalar stochastic prediction error $(Y_t - X_t'b_t|_{t-1})$ driving the filter is a zero mean and serially uncorrelated Gaussian process with variance $\sigma^2 f_t$, where $f_t = 1 + X_t'\Sigma_t|_{t-1}X_t$. The properties of the prediction error are conveniently described in Mehra (1970).

In economic applications, the prior estimate of β_t and Ω are usually not available, with which to begin the recursive estimation at the filter step. Garbade (1977) has suggested the algorithm can be initialized by using the first t observations to estimate b_{t+1}.

Random coefficients are obtained when $\Omega \neq 0$; thus, change at time t can be measured by the magnitude of Ω. The problem is then to estimate Ω. The variance ratio matrix Ω and the variance scalar σ^2 can be estimated by maximum likelihood approach (Schweppe, 1965; Garbade, 1977; Ledolter, 1979). Abraham and Ledolter (1983) have shown the log-likelihood function for the regression model with random walk coefficients. This approach requires specifying starting values of b_0 and Σ_0 in order to calculate K and then Ω.

$$L_c(\sigma^2, \Omega|\text{data}; b_0, \Sigma_0)\alpha - n \ln \sigma - \tfrac{1}{2}\sum_{t=1}^{T} f_t - \left(\tfrac{1}{2}\sigma^2\right)\sum_{t=1}^{T}\left(\hat{e}_t^2/f_t\right) \quad (13)$$

where

$$\hat{e}_t = Y_t - X_t'b_{t-1} \quad (14)$$

Maximizing this function with respect to σ^2 leads to the estimate:

$$\hat{\sigma}^2 = \frac{1}{T}\sum_{t=1}^{T}(\hat{e}_t)^2/f_t \quad (15)$$

Substituting this estimate into (13), the concentrated log-likelihood function can be obtained (Abraham and Ledolter, 1983):

$$L_c(\Omega|\text{data}; b_0, \Sigma_0)\alpha - \tfrac{1}{2}\sum_{t=1}^{T} \ln f_t - n \ln \hat{\sigma} \quad (16)$$

where $\hat{\sigma}$ and f_t are both implicit function of Ω. L_c is then a complicated non-linear function of Ω (Garbade, 1977). Thus, for given Ω, i.e. specify K, Eqs. (5) and (9) can be used to update the parameter estimate and to calculate f_t and $\hat{\sigma}^2$. Values of the unknown elements in the matrix Ω that maximize L_c can be found numerically.

If $K = 0$, then $\Omega = 0$ and β_t will be equal to β_{t-1} in the random walk model and the parameters are constant. If $K \neq 0$, then $\Omega \neq 0$, this implies random coefficient and structural change from one period to the next.

The Kalman filter technique has a potential use in estimating preferences change from one period to the next which traditional econometric methods do not appear well suited for the estimation. This technique can be implemented in numerous economic applications such as prediction, forecasts, and marketing analysis. The shortcoming of this technique stems from poor initial values of b_0 and Σ_0. However, this shortcoming has a declining effect in estimating random coefficients with time span. [1]

3. Model specification

The main objective of this paper was originally to assess structural change through a flexible

[1] For further reading, see Akaike (1970), Al-Ghamdi (1991), Al-Qunaibet et al. (1989), Brown and Lee (1992), Change (1977), Court (1967), Pope et al. (1980) and Tryfos and Tryphonopoulos (1973).

Table 1
Estimates of the Initial Values of the Demand for Meat in Saudi Arabia, 1972–1984

Commodity	Regression coefficients [a]					
	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\bar{R}^2$	D.W.	F-test
Poultry	0.357	−0.655	0.105	0.98	1.66	291.95
	(2.811) *	(−6.969) *	(6.309) *			
Red Meat	2.526	0.306	0.079	0.98	2.04	221.90
	(51.382) *	(7.107) *	(17.130) *			
Fish [b]	−1.264	−1.284	0.110	0.98	2.47	166.95
	(−1.872)	(−2.911)	(6.783) *			

[a] The price elasticity is given by β_1 and the growth rate is estimated by β_2. The t-statistics are given between parentheses.
[b] The available data for fish is over the period 1977–1984.
* Significant at 1% level of significance.

demand specification (i.e., prices, income, time, etc.). The Saudi economy phenomena in the past two decades should be taken into account at the model specifications. The first stage of the Saudi economy will introduce the initial values needed for applying Kalman filtering technique. Different attempts were implemented for the initial value estimates including prices to allow cross-elasticities, per capita of GDP, and time trend. However, these attempts were suffered strongly from multicollinearity problems, in addition to that family budget survey which reflects income effect does not comprehendible all details needed for pooling time series data with cross section data in the model. Economic variables which represent preference change should be considered. Thus, attention to the economy boom span should be brought out at estimating meat demand. This phenomena stimulated consumption in general to increase and preference to change. Therefore, it becomes an important for the authors to study preference change that measured by growth rate in per capita consumption for each meat commodity. Another important factor is the traditional meat consumption in Saudi Arabia which implicitly suggests separability among meat commodities.

The economic variables that should be included for building econometric model in this study are the following; per capita consumption for each meat commodity, real retail prices, and time trend. Time trend is used as a proxy of changing preferences in meat demand function. The assumption of adding an exogenous time trend is a common methods of treating changing preferences in demand relation (Johnson et al., 1984). Utilizing the independent assumption of error term (e_{ti}) in Eq. (1), the model can be specified as follows:

$$\text{Log}\, Y_{ti} = \beta_0 + \beta_1 \,\text{Log}\, X_{ti} + \beta_2 t + e_{ti} \tag{17}$$

$$e_{ti} \sim N(0, \sigma_i^2) \tag{18}$$

where Y_{ti} is the per capita consumption of commodity i at time t, X_{ti} the real retail price of commodity i at time t, (CPI, 1985 = 100), t time trend, e_{ti} disturbance term, with $i = 1, 2, 3$ commodities, and $t = 1, 2, \ldots, T$.

4. Empirical results

A Fortran 77 program has been designed [2] to estimate the meat demand function in two steps:

(1) Estimating the initial values of b_0 and Σ_0 by using the data over the initial period 1972–1984 for poultry and red meat, and over 1977–1984 for fish. The estimation method was done by assuming $K = 0$ over the initial period. Thus, Kalman filter results are asymptotically equivalent to ordinary least-squares estimates. The results are presented in Table 1. These results are considered as the prior information b_0 and Σ_0 in the Kalman filter.

[2] This program is especially designed for this problem, and it is available from the authors.

Table 2
Covariances of the initial values of the demand for meat in Saudi Arabia, 1972–1984

Commodity	Coefficients [a]				MSE
		$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	
Poultry	$\hat{\beta}_0$	0.1151E + 01	0.7125E + 00	0.6837E − 01	
	$\hat{\beta}_1$	0.7125E + 00	0.6308E + 00	0.9458E − 01	
	$\hat{\beta}_2$	0.6837E − 01	0.9458E − 01	0.1968E − 01	
					0.140E − 01
Red Meat	$\hat{\beta}_0$	0.1928E + 01	0.1528E + 01	0.9626E − 01	
	$\hat{\beta}_1$	0.1528E + 01	0.1476E + 01	0.1301E + 00	
	$\hat{\beta}_2$	0.9626E − 01	0.1301E + 00	0.1697E − 01	
					0.126E − 02
Fish	$\hat{\beta}_0$	0.1546E + 03	0.1008E + 03	0.3085E + 01	
	$\hat{\beta}_1$	0.1008E + 03	0.6602E + 02	0.2090E + 01	
	$\hat{\beta}_2$	0.3085E + 01	0.2090E + 01	0.8998E − 01	
					0.294E − 02

[a] The covariances are given by multiplying the coefficients times the mean square error (MSE).

The results satisfy standard tests, regression F-ratios and coefficient estimates are significant at 1% level. Durbin-Watson and correlation matrix indicate the absence of serial correlation in the residuals and multicollinearity among the explanatory variables. The results give an initial

Table 3
Yearly estimates of the demand for meat in Saudi Arabia, 1972–1984

Commodity	Years [b]	Regression coefficients [a]					
		Without structural change			Under structural change		
		$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$
Poultry	1985	0.357	−0.655	0.105	0.357	−0.655	0.105
	1986	0.328	−0.699	0.094	0.318	−0.714	0.090
	1987	0.311	−0.722	0.089	0.299	−0.740	0.084
	1988	0.303	−0.732	0.087	0.295	−0.745	0.083
	1989	0.283	−0.758	0.081	0.265	−0.786	0.075
	1990	0.266	−0.781	0.076	0.243	−0.818	0.068
	1991	0.253	−0.798	0.073	0.235	−0.829	0.065
Red meat	1985	2.526	0.306	0.079	2.526	0.306	0.079
	1986	2.498	0.270	0.074	2.480	0.248	0.071
	1987	2.507	0.281	0.075	2.514	0.288	0.076
	1988	2.477	0.244	0.071	2.443	0.200	0.065
	1989	2.337	0.067	0.049	2.110	−0.225	0.010
	1990	2.250	−0.053	0.033	2.023	−0.342	−0.006
	1991	2.203	−0.119	0.025	2.057	−0.298	0.000
Fish	1985	−1.264	−1.284	0.110	−1.264	−1.284	0.110
	1986	−1.878	−1.696	0.093	−1.919	−1.723	0.092
	1987	−2.284	−1.966	0.083	−2.374	−2.026	0.080
	1988	−2.362	−2.017	0.081	−2.393	−2.039	0.080
	1989	−2.510	−2.124	0.075	−2.736	−2.275	0.068
	1990	−2.538	−2.153	0.071	−2.876	−2.372	0.063
	1991	−2.543	−2.168	0.067	−3.020	−2.470	0.059

[a] The price elasticity is given by β_1 and the growth rate is estimated by β_2.
[b] The estimates of year (t) are used to forecast demand of year ($t+1$).

Table 4
Covariances of the regression coefficients of the demand for meat without structural change in Saudi Arabia, 1991

Commodity	Coefficients[(1)]					
		$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\sigma}^2$	L_c
Poultry	$\hat{\beta}_0$	0.9741E + 00	0.4699E + 00	0.1499E − 01		
	$\hat{\beta}_1$	0.4699E + 00	0.2960E + 00	0.2049E − 01		
	$\hat{\beta}_2$	0.1499E − 01	0.2049E − 01	0.3173E − 02		
					0.160E − 01	18.392
Red meat	$\hat{\beta}_0$	0.1388E + 01	0.8495E + 00	0.7462E − 02		
	$\hat{\beta}_1$	0.8495E + 00	0.6220E + 00	0.1831E − 01		
	$\hat{\beta}_2$	0.7461E − 02	0.1831E − 01	0.2293E − 02		
					0.173E + 00	6.396
Fish	$\hat{\beta}_0$	0.3996E + 02	0.2420E + 02	0.1363E − 01		
	$\hat{\beta}_1$	0.2420E + 02	0.1477E + 02	0.2844E − 01		
	$\hat{\beta}_2$	0.1363E − 01	0.2844E − 01	0.4450E − 02		
					0.110E − 01	18.824

[a] The covariances are given by multiplying the coefficients times the maximum likelihood estimate of σ^2.

information on price elasticities and consumption growth rate for each commodity item. The signs of estimated price elasticities are consistent with demand theory except for red meat. The direct price elasticity of red meat is positive implying a positive relationship between quantity consumed and its price. This is may due to the economy boom during this period. The constant term in Eq. (17) is interpreted as normalized scaling parameter so that negative sign for fish does not imply negative consumption. All growth rate of quantity demanded is expected to increase annually by 10.5%, 7.9% and 11% for poultry, red meat and fish, respectively. Covariance matrix of the initial period of the demand for meat is shown in Table 2.

(2) Estimating the demand for meat under structural change. The initial values of b_0 and Σ_0

Table 5
Covariances of the regression coefficients of the demand for meat under structural change in Saudi Arabia, 1991

Commodity	Coefficients [a]						
		$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\sigma}^2$	L_c	K
Poultry	$\hat{\beta}_0$	0.5827E + 01	0.2849E + 01	0.1036E + 00			
	$\hat{\beta}_1$	0.2849E + 01	0.1834E + 01	0.1417E + 00			
	$\hat{\beta}_2$	0.1036E + 00	0.1417E + 00	0.2426E − 01			
					0.519E − 02	20.301	0.839
Red meat	$\hat{\beta}_0$	0.2247E + 02	0.1404E + 02	0.2057E + 00			
	$\hat{\beta}_1$	0.1404E + 02	0.1050E + 02	0.3818E + 00			
	$\hat{\beta}_2$	0.2057E + 00	0.3818E + 00	0.4878E − 01			
					0.194E − 01	9.820	1.451
Fish	$\hat{\beta}_0$	0.1568E + 03	0.9696E + 02	0.9899E + 00			
	$\hat{\beta}_1$	0.9696E + 02	0.6037E + 02	0.7002E + 00			
	$\hat{\beta}_2$	0.9899E + 00	0.7002E + 00	0.3308E − 01			
					0.318E − 02	20.887	0.495

[a] The covariances are given by multiplying the coefficients times the maximum likelihood estimate of σ^2.

obtained from the first step can be used in the Kalman filter and maximum likelihood to investigate structural change over the period 1985–1991. The results of estimating demand for meat with and without structural change are presented in Table 3. K is assumed to be zero to estimate the regression coefficients without structural change. This implies $\Omega = 0$ for $t = 1985–1991$. Kalman filter with different K ($\Omega \neq 0$, $t = 1985–1991$) is applied to estimate the random coefficients, implying structural change in meat demand. The maximum likelihood Eq. (16) gives $K = 0.839$ for poultry, $K = 1.451$ for red meat, and $K = 0.459$ for fish (Table 5). This implies that random coefficients were more introduced into red meat than poultry and fish. Thus, important structural change was identified for red meat more than poultry and fish. Tables 4 and 5 illustrate the covariance matrix, concentrated log likelihood function, and maximum likelihood estimate of σ^2 for demand meat with and without structural change, respectively. The diagonal of covariance matrix ($\Sigma_t|_{t-1}$) under structural change (Table 5) has larger values than the diagonal of covariance matrix (Σ_{t-1}) without structural change (Table 4). This is a premium magnitude as a result of adding Ω to Σ_{t-1}. Concentrated log likelihood function has higher values with than without structural change as shown in Tables 4 and 5. This supports the capability of the dependent on Kalman filter technique of detecting structural change. The variance estimates are substantially minimized in the Kalman filtering techniques when $\Omega \neq 0$ (Table 6).

Table 6
Estimates of the demand for meat in Saudi Arabia, 1991

Commodity	Regression coefficients [a]			
	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\sigma}^2$
Without structural change ($\Omega = 0$):				
Poultry	0.254	−0.798	0.073	
	(2.030)	(−11.595) *	(10.257) *	
				0.01600
Red meat	2.203	−0.119	0.025	
	(4.499) *	(−0.362)	(1.249)	
				0.17300
Fish	−2.543	−2.168	0.067	
	(−3.844) *	(−5.390) *	(9.566) *	
				0.01100
Under structural change ($\Omega \neq 0$):				
Poultry	0.235	−0.829	0.065	
	(1.354)	(−8.496) *	(5.808) *	
				0.00519
Red meat	2.057	−0.298	0.000	
	(3.113) *	(−0.660)	(−0.013)	
				0.01940
Fish	−3.020	−2.470	0.059	
	(−4.275) *	(−5.636) *	(5.710) *	
				0.00318

[a] The price elasticity is given by β_1 and the growth rate is estimated by β_2. The t-statistics are given between parentheses.
* Significant at 5% level of significance.

5. Conclusion

The accuracy of result estimations are essentially rely on the initial parameter values. The change in the coefficient estimates are corresponding to the magnitude of K. The higher magnitude of K, the more structural change is occurred.

Structural change in poultry (fish) are reflected in a price elasticity increase from 0.665 (1.284) in 1985 to 0.829 (2.47) in 1991, and a decrease in growth rate from 10.5% (11%) to 7% (5.9%) during the same period, respectively. The poultry and fish direct price elasticities are higher under structural change than without structural change, while growth rate is less with structural change than without structural change. These findings indicate poultry is more necessary than fish consumption. Thus, fish market is subject to large variation as supply fluctuate than poultry market. The per capita consumption of poultry and fish is increasing while growth rate is decreasing, which implies change in consumption preferences. The consumption growth rate under structural change is less and more realistic than without structural change in the long run.

The correct sign of price elasticity of red meat appeared in 1989 and 1990 for under and without structural change, respectively. The small price elasticity is consistent with the traditions, including social and religion activities, of red meat consumption in Saudi Arabia. Therefore, consumption is not sensitive with red meat prices.

The growth rate became zero at 1989, implying per capita consumption takes constant pattern. Finally, the results are consistent with meat consumption preference and pattern in the last few years with which increasing per capita consumption in poultry and fish and zero growth rate in red meat consumption. These results indicate long-run growth prospects for the poultry and fish industry and moderate in red meat industry. Thus, these findings have important implications for market analysis and projections of meat demand in Saudi Arabia.

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