

An Econometric Model of the Aggregate Motor Insurance Market in the United Kingdom

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ABSTRACT

Annual data for 1950 through 1984 are used to estimate a model of the aggregate motor insurance market in the United Kingdom. Because the demand for motor insurance is a derived demand, an appropriately specified model can use this information to identify the supply schedule in a recursive system. However, the durability of motor vehicles must be taken into account in modeling the exogenously determined demand schedule. Time series models of the ARIMA type, as suggested by the theory, are compared with the popular econometric approach of cointegrating regressions and error correction models. The results suggest that the error correction models provide an adequate description of the data.

Introduction

Although individuals' insurance decisions have attracted a great deal of theoretical interest from economists, except for Sherden (1984) applied studies related to motor insurance have been rather scarce. This is surprising, because other issues relating to car ownership—taxation, road usage, and the purchasing decision itself—have been extensively examined. Because motor insurance is a compulsory requirement in the United Kingdom under the Road Traffic Acts, it is of interest to examine this particular component of expenditure.

It would be highly desirable to have access to microdata relating to expenditure on motor insurance and related products and to have detailed data on insurers. Data of this type are not available in sufficient quantities to enable one to conduct a thorough analysis. At the aggregate level, a longer time series of data can be utilized, and it is of interest to examine the interaction between demand and supply at this level of aggregation. For example, government regulation applies to the entire market, and so some

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knowledge of its workings is necessary for the successful implementation of specific economic policies. Forecasting is another area where an aggregate model might prove useful.

Despite certain attractions (and the necessity) of working with aggregate data, there are drawbacks. Changes in the microstructure of a model are always ignored in studies using aggregate data. In this case, one feature not captured is the distinction between third-party and comprehensive coverage. An increase in the number of young drivers, for example, is likely to lead to more third-party coverage, a feature not represented in the aggregate model. Aggregate models are usually based on the underlying assumption of a representative agent whose decision problem is captured by a stylized mathematical model. At the empirical level, aggregation issues are typically discounted, and the model is estimated as if the microproperties carry over to the macroparameters. Although this may be unrealistic, data limitations often necessitate such an approach, which does, at least, give some structure and a theoretical basis to the analysis.

This article argues that using a representative agent model derived from microeconomic theory to capture the supply side of the model is unrealistic, mainly because insurers base their pricing behavior on expectations and because firms are inherently heterogeneous. The approach adopted here is intended to be flexible enough for the data to determine the precise form of the "supply" side. More commonly used models of demand are considered, but only the broad implications of the theory are tested with the data. The empirical work uses the econometric concept of cointegration to analyze the time series properties of the data, leading to a parsimonious error correction model. The objective is to develop an empirical model in which the estimated parameters have desirable statistical properties. The approach is to consider appropriate theoretical models and then to specify empirical models that reflect the important implications of the theory.

The U.K. Motor Insurance Market

The Supply of Motor Insurance

Motor insurance in the United Kingdom is provided mainly by large multiple line insurers and by syndicates of underwriters operating through the Lloyd's of London market. In 1983, for example, there were 315 companies licensed by the Department of Trade and Industry to provide motor insurance in the United Kingdom in addition to 43 Lloyd's syndicates (Department of Trade and Industry, 1984; Rowe and Pitman, 1985). Of the 315 companies, the top twenty (in terms of premium income) accounted for 91 percent of the U.K. motor insurance market in 1983, while the 43 Lloyd's syndicates accounted for 14 percent (British Insurance Association, 1983; Rowe and Pitman, 1985). Although market share is concentrated in the hands of a relatively small number of insurers, there is fierce premium

rate competition. Rates may diverge by up to 67 percent for the same risk,¹ but this divergence, at least in part, reflects the different underwriting policies of competing insurers. Insurers are not compelled to underwrite any risk offered to them; they are quite at liberty to impose severe premium surcharges and experience ratings in order to control the type of risks they insure.

With such a large divergence in premium rates for some risks it is not surprising that there is a large network of intermediaries (brokers) who attempt to find the most competitive rates for their clients. The brokers receive a commission from the insurer with whom the risk is placed and sometimes charge the client an additional administrative fee for their services. The matching of risk (client) with insurer is a complex process and is likely to be suboptimal in practice due in part to an absence of perfect information about the current state of the market.

Deriving a suitable model for the supply of motor insurance is not a straightforward application of the theory of the firm in microeconomic analysis. Insurers provide a service rather than a physical product, and they determine premiums based on expectations about future claims frequencies and claims costs. It is likely, therefore, that realized underwriting results will contain a large stochastic element arising from this inherent uncertainty. Thus, a model of a representative firm when aggregated for use with industry-wide data is subject to an even larger stochastic component, and the heterogeneity of firms suggests that such an aggregated model may be inconsistent with the underlying theory. Furthermore, it is doubtful that insurers operate efficiently enough for the usual models (based on perfect information and optimizing behavior) to hold. Evidence for the property-liability insurance industry in the United States obtained by Weiss (1991) suggests that allocative and scale inefficiency costs can be as much as one-third of premium income.

In view of the inappropriateness of the standard microeconomic theory of the firm for this particular industry, a more heuristic approach will be adopted for deriving a "model" of supply that can be applied to the time series data in this study. By "supply" I mean an empirical relationship between the (average) premium, denoted P , and the total number of vehicles being insured, denoted K , in addition to any other explanatory variables. The supply curve is usually associated with the portion of the marginal cost curve above the level of minimum average variable cost. For U-shaped average costs, the relevant section of the marginal cost curve is an increasing function of K , so the question is whether this is a suitable description of costs at the industry level for this particular market. It seems reasonable to assume that beyond a certain point, at least in the short run, returns to scale will decrease because of rising administrative costs, for

¹ Expressed as the excess of the highest rate over the lowest rate as a percentage of the lowest rate (Rowe and Pitman, 1985).

example, and inefficient use of resources, which will be associated with rising marginal costs. Because this study regards this relationship as mainly an empirical matter to be investigated, a specification is required that is not constrained by an unrealistic underlying theory. The intention is to let the data guide the search for an appropriate empirical specification.

The following general form of aggregate supply function for the industry is considered:

$$P_t = \alpha K_t + Z'_t \psi + e_t, \quad (1)$$

where Z_t is a vector of explanatory variables, and e_t is a random disturbance term (the subscript t denotes the discrete time period). The vector Z_t captures other relevant information that may influence the cost structure, and hence the price-setting behavior, of insurers. Because K_t is difficult to observe (as with any durable good), it is necessary to eliminate K_t to obtain an equation involving N_t , purchases of new motor vehicles, about which more reliable data is available. This is achieved using the stock depreciation relationship

$$K_t = (1-\delta)K_{t-1} + N_t, \quad (2)$$

where δ is the (constant) rate of depreciation. Using equation (2) to eliminate K_t in equation (1) yields

$$P_t = (1-\delta)P_{t-1} + \alpha N_t + Z'_t \psi - (1-\delta)(Z'_{t-1} \psi) + e_t - (1-\delta)e_{t-1}, \quad (3)$$

which is an autoregressive moving average model with exogenous variables (an ARMAX model). This model forms the starting point in the empirical analysis of the supply side of the model. However, it is doubtful whether it is possible to obtain reliable estimates of the underlying structural parameters in this restricted ARMAX model from a sample of only 35 observations. This issue is discussed in more detail below.

The Demand for Motor Insurance

The demand for motor insurance in the United Kingdom is essentially a derived demand, in that a minimum level of coverage is compulsory. This minimum level of coverage relates to third-party risks, but many motorists choose comprehensive policies, which also cover fire and theft risks and accidental damage to the insured's own vehicle. The available data is an aggregate of all types of coverage, so it is not possible to model the underlying choice that the motorist makes. Because the number of vehicles to be insured is determined outside the motor insurance market, the demand schedule should be (perfectly) inelastic with respect to the insurance premium. This is important information that can be used in the modeling of this particular market. Shifts in the demand schedule are therefore exoge-

nously determined and can be captured by appropriate reference to models of durable goods demand.²

The aim is to model the demand for car ownership. One of the best known models relating to the demand for durable goods is the stock adjustment model, underpinned by the depreciation relationship given in equation (2) above. Since the total number of vehicles insured over time (K_t) is typically unobservable, some mechanism is required in order to derive an empirically implementable equation in terms of the observable variable of purchases of new motor vehicles (N_t). This is usually achieved by assuming that, for each period, some fraction γ ($0 \leq \gamma \leq 1$) of the deviation of the actual stock from its desired level K_t^* is closed:

$$K_t - K_{t-1} = \gamma(K_t^* - K_{t-1}) + u_t, \quad (4)$$

where u_t is a random disturbance term. An assumption relating the unobservable desired stock K_t^* to a vector of observable variables X_t completes the model:

$$K_t^* = X_t' \beta, \quad (5)$$

where β is a vector of parameters to be estimated along with δ and γ . The solution to equations (2), (4), and (5) is given by

$$N_t = (1-\gamma)N_{t-1} + \gamma(X_t' \beta) - \gamma(1-\delta)(X_{t-1}' \beta) + u_t - (1-\delta)u_{t-1}, \quad (6)$$

which is an ARMAX model with certain parameter restrictions imposed. The common moving average property exhibited by equations (6) and (3), which arises from the common underlying depreciation relationship, can be tested empirically in an appropriate system of equations.

Although this general type of stock adjustment model has been widely accepted since the early work of Stone and Rowe (1957) and Houthakker and Taylor (1966), it has recently been criticized by, among others, Bar-Ilan and Blinder (1988). The latter authors argue that the idea of continuous adjustment, as implied by equation (4), is unrealistic at the level of the individual agent, since typically one observes that stocks of durable goods are held until they have depreciated to a certain low level, at which point a new purchase takes place. It is hard to justify why, at the microlevel, an individual would wish to make up only some proportion γ of the deviation from the desired stock. So rather than continuous adjustment taking place, the process of adjustment behaves like a ratchet—adjustment costs are “lumpy.” The so-called (S,s) model developed by Bar-Ilan and Blinder is a life cycle model of demand for durable goods. Although this model will

² In reality, premiums are not so low that they have *no* effect on individuals' purchasing decisions. However, it is unlikely that a vehicle's insurance premium is a major determinant of an individual's decision to purchase it. Whether the premium is a significant determinant of demand for motor vehicles can be tested empirically and is addressed below.

not be treated in detail here, their equation that corresponds to equation (6) is given by

$$N_t = N_{t-1} + A(1+\delta)(y_t^p - y_{t-1}^p) - A(y_{t-1}^p - y_{t-2}^p) + v_t, \quad (7)$$

where y_t^p denotes permanent income, and v_t is a moving average disturbance term depending on δ . This suggests that for durables, past income is important in predicting future consumption, contrary to Hall's (1978) well established results for nondurable consumption. However, the empirical results obtained by Bar-Ilan and Blinder provide less than convincing support for this model.

Another difficulty with the empirical implementation of the stock adjustment model concerns the estimation of the depreciation rate δ . Apart from the fact that δ is assumed to be constant through time, it is not clear that a physical depreciation rate is actually being estimated. As pointed out by Bergstrom and Chambers (1990) in their continuous time model of durable goods demand, the parameter δ may also reflect the strength of consumers' preferences for new goods in addition to purely physical depreciation. Thus, if consumers are eager to acquire new motor vehicles, the current stock will have a higher depreciation rate than the purely physical rate as perceived by the consumers. The resulting estimate of δ will consequently be higher than would otherwise be expected.

One of the features to emerge from the above models is that purchases of new cars should roughly follow an autoregressive moving average (ARMA) model, possibly with exogenous variables. Indeed, Mankiw (1982) showed that N_t should follow an ARMA(1,1) process, and this clearly can be tested empirically. Our starting point is therefore to see whether an ARMA model is an adequate representation of the demand for car purchases. Additional variables may be added to the model, such as interest rates, income, car prices, etc., to assess their contribution to the explanation of the observed pattern of behavior. As with the supply equation, some care needs to be taken in interpreting the estimates of an ARMAX model from just 35 observations, particularly when the equation, such as equation (6), is subject to parameter restrictions.

Econometric Considerations

Equations (6) and (3) specify a basic demand and supply model that must be estimated as a system in order to impose the cross-equation restrictions involving the parameter δ , in addition to the within-equation restrictions involving the remaining parameters. With just 35 observations available to estimate this restricted vector ARMAX system, it is doubtful whether the results would be particularly robust to even slight changes in the specification of the underlying equations. Despite this limitation, it is still possible to test the common moving average property exhibited by equations (6) and (3), which is an important implication of the theory. The empirical approach is to treat each equation separately in order to find an appropriate

ARMA-type representation, and then to test for the inclusion of exogenous variables (the elements of the vectors X_t and Z_t). The two preferred equations can then be estimated as a system in which the test for the equality of the moving average (MA) coefficients can be conducted.

An alternative approach to dynamic econometric modeling is to focus separately on the short- and long-term properties of the model. The theory presented above specifies equilibrium conditions; the resulting dynamics are generated primarily by the stock depreciation equation (2) and, for the demand equations, by the ad hoc adjustment equation (4). The actual dynamic behavior observed may be very different from that implied by these particular specifications and is best determined by the data rather than imposed by the theory. It would therefore be desirable to allow greater flexibility in the empirical specification of the dynamics, while using the theory to specify the (static) long-term equilibrium.

The time series properties of economic data have received a great deal of attention, particularly in regard to the stationarity of the data.³ We say that a series is integrated of order k if it needs to be differenced k times to become stationary. Thus, if a variable Y_t requires differencing once in order to achieve stationarity, then Y_t is integrated of order one, which is denoted $Y_t \sim I(1)$. The first difference of Y_t , denoted $\Delta Y_t = Y_t - Y_{t-1}$, is therefore stationary and we may write $\Delta Y_t \sim I(0)$. The process Y_t is then said to contain a unit root.

The most popular empirical test to detect the presence of nonstationarity in a time series is the Dickey-Fuller (DF) test. This is a test of the hypothesis $\beta = 0$ against the alternative $\beta < 0$ in the equation

$$\Delta Y_t = \beta Y_{t-1} + u_t, \quad (8)$$

where u_t is a stationary random disturbance. Clearly, if $\beta = 0$, then $\Delta Y_t = u_t$, which is stationary, and hence $Y_t \sim I(1)$. If $\beta > 0$, the process Y_t is explosive, but $\beta < 0$ ensures that $Y_t \sim I(0)$, since $Y_t = (1+\beta)Y_{t-1} + u_t$ and $(1+\beta) < 1$ in this case.⁴ The statistic used for testing the null hypothesis $H_0: \beta = 0$ against the alternative $H_1: \beta < 0$ in equation (8) is the ratio $t = \beta/\sigma(\beta)$, where $\sigma(\beta)$ denotes the standard error of β . Because Y_t is nonstationary under the null hypothesis, this statistic no longer has the conventional t -distribution, and so the critical values derived by Fuller (1976) must be used. The DF test can also be conducted with a constant term and a time trend in equation (8), which in turn constitutes a different set of critical values. The augmented Dickey-Fuller (ADF) test includes lagged dependent variables in equation (8) in order to "whiten" the residuals and is also

³ A variable is said to be stationary if its mean and variance are constant over time and its covariances are functions only of the lag length and not of time alone. More mathematically, the sequence $\{Y_t; t = 1, 2, \dots\}$ is stationary if $E(Y_t) = \mu$, $\text{var}(Y_t) = \sigma^2$, and $\text{cov}(Y_t, Y_{t-s}) = \sigma_s$ for $s \geq 1$.

⁴ An autoregressive process $Y_t = \alpha Y_{t-1} + u_t$ is stationary provided that $-1 < \alpha < 1$; in terms of β in the text we require $-1 < 1+\beta < 1$ or $-2 < \beta < 0$.

based on the usual t -statistic using the appropriate critical values in Fuller (1976).

An important concept that arises from the modeling of integrated time series is that of cointegration. Consider a vector X_t of n random variables, each of which has been found to be $I(k)$. These variables are said to be cointegrated if a linear combination of these variables is integrated of a lower order than k , that is, if $\alpha'X_t \sim I(k-b)$, where $b \geq 1$. The n -vector α is known as the cointegrating vector and provides information about the stable (long-term) relationship between the nonstationary elements of X_t . In empirical investigations many economic time series have been found to be $I(1)$, and so tests for cointegration focus on whether there exists a linear combination of the variables which is $I(0)$ (stationary).

A common example of cointegration is the relationship between consumers' expenditure and income, which shall be denoted by C_t and Y_t , respectively. Although both variables are widely regarded as being $I(1)$ processes, it is observed that they tend to move closely together over time, which would not occur unless the two variables were cointegrated. The most common method of testing for cointegration between the two $I(1)$ variables C_t and Y_t is to estimate by least squares the equation

$$C_t = \theta Y_t + u_t \quad (9)$$

and then test to see whether the residuals $u_t = C_t - \hat{\theta}Y_t$ are stationary. If $\hat{u}_t \sim I(0)$, then the linear combination $C_t - \hat{\theta}Y_t$ represents a cointegrating relationship. Stationarity of u_t can be tested using the DF and ADF test procedures.

Because the cointegrating relationship represents only the long-term (or equilibrium) relationship between the variables, one must obtain an appropriate dynamic model that can capture the short-term adjustment in addition to the long-term behavior. This is usually achieved in the context of cointegrated models by the estimation of an error correction model (ECM). For the consumption-income example such a model might take the form

$$\Delta C_t = \sum_{i=1}^m a_i \Delta C_{t-i} + \sum_{i=0}^p b_i \Delta Y_{t-i} + \lambda \hat{u}_{t-1} + \varepsilon_t, \quad (10)$$

where ε_t is a stationary random disturbance. Note that all the regressors and the regressand in equation (10) are stationary, and hence conventional hypothesis tests are valid for this model. The lagged terms involving ΔC_t and ΔY_t attempt to capture purely short-term fluctuations, whereas the term $\hat{u}_{t-1}$ allows C_t to respond to the observed deviation from long-term equilibrium in the previous period. The adjustment parameter λ is expected to be negative so that, *ceteris paribus*, C_t will increase ($\Delta C_t > 0$) in response to C_t being less than its equilibrium or desired level ($\hat{u}_{t-1} < 0$) in the previous period. In addition to being intuitively appealing, such models have been found to be successful in a wide variety of empirical applications. For a

recent application of this methodology see, for example, Baba, Hendry, and Starr (1992).

The above approach to dynamic modeling, in which a long-term solution is embedded within a dynamic model, is entirely consistent with the theory developed above, for if there is to be a stable long-term equilibrium between the demand for, and supply of, motor insurance, then these variables should be cointegrated. In the long run, replacement demand for motor vehicles is equal to depreciation of the stock, so that $N_t = \delta K_t$. The substitution of $K_t = (1/\delta)N_t$ into equations (5) and (1) yields the following system of equations:

$$N_t = \delta X_t' \beta + \varepsilon_{1t} \quad (11)$$

$$P_t = (\alpha/\delta)N_t + Z_t' \psi + \varepsilon_{2t}, \quad (12)$$

where these equations now contain random disturbances ε_{1t} and ε_{2t} . Equations (11) and (12) specify the cointegrating relationships. If N_t , P_t , and the elements of X_t and Z_t are found to be nonstationary $I(1)$ processes, then if $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})'$ is $I(0)$ (stationary), we can regard this system as adequately specifying the long-term or equilibrium relationship. In the empirical work one must therefore conduct the tests for unit roots in these variables and then attempt to find appropriate specifications for equations (11) and (12) before fitting the dynamics to the error correction model.

The system of equations (11) and (12) is recursive; N_t is determined by equation (11), and in turn it determines P_t through equation (12). Although the random disturbances in these two equations are likely to be correlated, which would typically require the equations to be estimated jointly, they can in fact be estimated in two stages. First, the equation determining N_t is estimated, and the fitted values from this equation may be used in place of N_t in determining P_t in stage two. If, on the other hand, the disturbances are uncorrelated, the system may be estimated as two separate single equations using a well-known result regarding recursive systems (see, for example, Johnston, 1984, p. 468). The validity of this simplifying assumption can be tested empirically. Indeed, the coherence of the data with this recursive specification (the question of whether P_t influences N_t) can be confronted by testing for the inclusion of P_t as a regressor in the demand equation.

Given that appropriate cointegrating relationships can be found based on equations (11) and (12), suitable ECM specifications must be derived in order to account for short-term fluctuations in behavior. The following general forms of ECM are considered:

$$\Delta N_t = \sum_{i=1}^m a_i \Delta N_{t-i} + \sum_{i=0}^p b_i' \Delta X_{t-i} + \lambda \hat{\varepsilon}_{1,t-1} + v_{1t} \quad (13)$$

$$\Delta P_t = \sum_{i=1}^q f_i \Delta N_{t-i} + \sum_{i=1}^r c_i \Delta P_{t-i} + \sum_{i=0}^s d_i' \Delta Z_{t-i} + \eta \hat{\varepsilon}_{2,t-1} + v_{2t}, \quad (14)$$

where b_i and d_i are appropriately dimensioned vectors of parameters, and λ and η are the adjustment parameters. A general-to-specific modeling strategy is adopted by estimating the general forms given by equations (13)

and (14) and then conducting appropriate t-tests and F-tests to determine which of the regressors are important in determining the short-term changes in N_t and P_t . The aim is to derive a parsimonious dynamic model that can explain the observed short-term behavior and that is consistent with a stable long-term equilibrium between the variables.

The empirical work takes into consideration the possible changes in the underlying structure of the motor insurance industry due to price regulation in the 1970s and the period of instability in the late 1960s and early 1970s. Although these events are likely to affect the supply side rather than the demand side of the model, it is possible that the oil price shocks of 1974 and 1979 had a significant impact on the demand for motor vehicles. These effects are best captured by appropriately defined dummy variables. In the empirical work, tests for changes in both the constant terms and the slope parameters in equations (11) and (12) are conducted to allow for possible structural change. Similar tests are applied to the dynamic model defined by equations (13) and (14).

Empirical Results

Logarithmic transformations of all variables are taken, which are denoted by lower case letters, so that $x_t = \ln(X_t)$ for any variable X_t . I begin by examining the time series properties of the data, in particular testing for unit roots. Table 1 contains the DF and ADF test statistics for the logarithms of the five time series used in this article: purchases of new cars (n_t), average motor insurance premium (p_t), personal disposable income (y_t), average price of a new car (c_t), and real rate of interest (r_t), the latter not being in logarithmic form. Since the DF and ADF tests are one-sided, values of the test statistic less than the critical values shown are required in order to reject the null hypothesis of nonstationarity in favor of stationarity of the appropriate series. Of the five series, only the real rate of interest is stationary, since the test statistic is below the critical value. This suggests

Table 1
Unit Root Tests

Variable	Test Statistic ^a	Critical Value (5%) ^b
n_t	ADF(2) = -3.05	-3.60
p_t	ADF(2) = -2.18	-3.00
y_t	ADF(1) = -1.97	-3.60
c_t	DF = -2.04	-3.60
r_t	DF = -4.21	-1.95

Note: n_t = purchases of new cars, p_t = average motor insurance premium, y_t = personal disposable income, c_t = average new car price, and r_t = real rate of interest.

^a ADF(k) denotes the Augmented Dickey-Fuller statistic in a regression with k lagged differences; DF is the usual Dickey-Fuller statistic.

^b From Fuller (1976).

that the ARMA models should contain unit roots, and hence the series would be best modeled as autoregressive integrated moving average (ARIMA) processes.⁵

The results of estimating the time series models corresponding to the demand and supply equations are summarized in Table 2 as likelihood ratio (LR) test statistics. Values of the test statistics greater than the χ^2 critical values suggest that the null hypothesis should be rejected in favor of the specified alternative. In each case, an ARIMA(0,1,1) model, which is an ARMA(1,1) model with an AR coefficient of unity, appears to be an appropriate description of the data. The lower panel of Table 2 displays the LR test statistics for the inclusion of additional variables into the ARIMA(0,1,1) models. The only variables achieving anything near significance are the real rate of interest (r_t) and r_{t-1} , although even these are rejected at the 5 percent level. However, this indicates that the real interest rate may be an important variable in the specification of the error correction models.

Table 2
Likelihood Ratio Test Statistics for Time Series Models

Null	Alternative	Demand	Supply	Critical Value (5%)
ARMA(1,1)	ARMA(2,1)	0.0698	0.1070	3.841
ARIMA(0,1,1)	ARMA(1,1)	2.4424	0.0594	3.841
ARIMA(0,1,1)	ARIMA(1,1,1)	0.0128	0.0884	3.841
Variables Added to ARIMA(0,1,1)				
Δy_t and Δc_t		0.3720	—	5.991
r_t and r_{t-1}		4.5350	5.5358	5.991
Δn_t and Δc_t		—	0.0390	5.991
Δn_t , r_t , and r_{t-1}		—	5.7606	7.815

Note: n_t = purchases of new cars, y_t = personal disposable income, c_t = average new car price, and r_t = real rate of interest.

The ARIMA(0,1,1) models estimated are given by

$$\Delta n_t = u_t + 0.3940u_{t-1} \quad \hat{\sigma} = 0.1381 \quad (15)$$

(0.1551)

$$Q(1) = 0.2491 \quad Q(4) = 3.9315$$

$$\Delta p_t = e_t + 0.5445e_{t-1} \quad \hat{\sigma} = 0.0563 \quad (16)$$

(0.1493)

$$Q(1) = 0.0328 \quad Q(4) = 2.3013,$$

⁵ If Y_t contains a unit root, so that ΔY_t is stationary, an ARIMA model is of the form $a(L)\Delta Y_t = b(L)u_t$, where $a(L)$ and $b(L)$ are polynomials in the lag operator L such that $L^j Y_t = Y_{t-j}$ for integer j .

where figures in parentheses are standard errors, $\hat{\sigma}$ is the standard error of the residual process, and $Q(j)$ is a Ljung-Box portmanteau statistic to test for serial correlation of up to j th order in the residuals. The portmanteau statistic $Q(j)$ is asymptotically distributed as χ_j^2 under the null hypothesis of no serial correlation up to order j .

One implication of the stock adjustment type models is that the moving average coefficients in equations (15) and (16) should be equal. Imposing this restriction and estimating the equations jointly yields a common parameter estimate of 0.4483 with a t -statistic of 3.6121. The likelihood ratio statistic for testing the null hypothesis that the two MA coefficients are the same against the alternative where the two MA coefficients are different equals 0.2457, which does not reject the null hypothesis. This particular implication of the stock adjustment/durable goods theory is therefore supported by the data.

Although the time series models are consistent with economic theory, they are not very helpful in determining equilibrium conditions in the motor insurance market. It is in this sphere that error correction models are intuitively very appealing, because they offer a dynamic model of nonstationary data that possesses a long-term equilibrium. In order to do justice to the applied work, it is necessary to allow for the possibility of changes in the underlying structural equations due to regulation, legislation, and exogenous shocks, as mentioned above. Dummy variables are defined to capture the period of price regulation from 1973 through 1979 (D7379) and the general period of change in the economy from 1973 through 1984 (D7384), which roughly coincides with the first oil price shock. An additional dummy variable representing 1969 (D69) was also found to be important, as there appeared to be an outlier in the residuals of virtually all models for this year, which coincides with the height of the period of insurance company collapses. These dummy variables may also be incorporated to capture changes in the slope parameters, in addition to the constant terms in the regressions, by defining for a variable x_t a new variable $z_t = x_t D_t$. Because the variables used for estimation are mainly in logarithms, this procedure allows for changes in the corresponding elasticities.

We begin with the cointegrating regressions defined by equations (11) and (12) (see Table 3). There is strong evidence in the demand equation of a structural break occurring in 1973, which affected not only the intercept term in the regression, but also the income and interest rate elasticities of demand. Post-1973 behavior is characterized by a marked fall in both the income and interest rate elasticities. Note too the absence of price effects in this equation. A test for the addition of both p_t and c_t and the appropriate dummy terms yielded an $F(4,25)$ statistic of 0.2418, which is below the 5 percent critical value of 2.759. This rejection of including p_t in the demand equations supports the theoretical model, which is recursive.

Table 3
Cointegrating Regressions

Regressors	Demand (n_t)	Supply-1 (p_t)	Supply-2 (p_t)
Constant	-14.4848 (1.9752)	4.3173 (0.1753)	5.3785 (0.3543)
D69		-0.1712 (0.0688)	
D7379		-4.9367 (1.6319)	-12.6700 (2.9368)
D7384	21.1525 (2.5493)		
y_t	2.0810 (0.1946)		
$y_t \times D7384$	-2.0133 (0.2398)		
r_t	0.0790 (0.0150)		-0.0146 (0.0043)
$r_t \times D7384$	-0.0655 (0.0183)		
c_t			-0.3301 (0.0556)
n_t		-0.1563 (0.0261)	
$n_t \times D7379$		0.6645 (0.2210)	
$n_t \times D7384$		0.0295 (0.0052)	
$n_t \times D7379$			1.6993 (0.3958)
$n_t \times D7384$			0.0363 (0.0053)
R^2	0.9075	0.7020	0.7286
DW	1.0895	1.7783	1.6641
σ	0.1864	0.0669	0.0639
DF	-3.9311	-5.2164	
ADF(1)			-5.3162

Note: Standard errors are in parentheses.

The two supply equations reported in Table 3 correspond to the cases where the demand and supply disturbances are regarded as independent and correlated, respectively. The results in the final column are estimated using the fitted values from the demand equation. Both equations indicate that the period of price regulation in the mid-1970s was important with a large increase in the supply elasticity. The unusual feature in the first equation is

Table 4
Estimates of Error Correction Model

Regressors	Demand (Δn_t)	Supply (Δp_t)
Constant	0.1291 (0.0215)	0.0083 (0.0071)
D69	-0.2321 (0.0726)	-0.0826 (0.0380)
Residual _{t-1}		-0.6089 (0.1298)
Residual _{t-2}	-0.3174 (0.0839)	-0.3821 (0.1295)
Δr_t	0.0198 (0.0033)	
Δr_{t-2}	-0.0163 (0.0061)	
$\Delta r_{t-2} \times D7384$	0.0197 (0.0063)	
Δy_t	1.9650 (0.5210)	
Δy_{t-1}	-2.8999 (0.4920)	
Δc_{t-1}		-0.3170 (0.1206)
Δp_{t-1}		0.5382 (0.1333)
Δn_{t-2}	-0.2046 (0.1027)	
σ	0.0680	0.0365
R^2	0.8422	0.7199
DW	1.9563	2.2978
SC: χ^2_1	0.0001	1.9844
F: χ^2_1	0.0421	3.0393
N: χ^2_2	2.0221	2.0739
H: χ^2_1	0.3264	1.4938

Note: SC is a Lagrange Multiplier (LM) test for first order serial correlation; FF is a test for functional form; N is a test for normality of the residuals based on their skewness and kurtosis; and H is a test for heteroscedasticity. All of the tests are asymptotically distributed as χ^2_j under the null hypothesis, where j denotes the degrees of freedom.

the negative coefficient on n_t , which suggests that the equation may be misspecified. This raises the issue of identification, because without further information it is not clear that an actual supply equation is being estimated. The results in the final column overcome this problem and suggest that in the pre-1973 period, the supply curve was independent of n_t . However, the post-1973 period is somewhat different with a slightly inelastic supply

curve. Since the two versions of the supply equation are non-nested, an appropriate test is conducted to discriminate between the two specifications. The appropriate non-nested tests all favor the second specification, as do the Schwarz and Akaike Information Criteria. This further supports the view that the cointegrating model should be estimated as a recursive system in which the residuals are not contemporaneously independent. In view of these results, the ECMs that are considered will concentrate exclusively on this latter specification.

The estimated ECMs for the demand and supply equations are displayed in Table 4. Both equations appear to be well specified with the influence of a break in 1969 still evident. The residuals pass the usual diagnostic tests, and have much smaller standard errors than in the time series models. There is evidence of considerable lags by both consumers and insurers in adjusting their respective behaviors, as is highlighted by the significant second lag on the error correcting terms. Overall, these equations seem to adequately represent the data.

Conclusions

This article empirically models the motor insurance market in the United Kingdom using annual time series data from 1950 through 1984. A heuristic approach is adopted for specifying the supply side of the model, for it is argued that the standard microeconomic theory of the firm is not a good representation of the actual price-setting decisions undertaken by individual insurers. Actual decisions are based on expectations about future claim frequencies and claim costs, resulting in a divergence of observed behavior from the expected outcome. Furthermore, aggregation over a large number of heterogeneous firms would cast suspicion on the results obtained from a representative agent model. For these reasons a linear (in logarithms) function is used in the empirical work so that the data can determine the precise form of the supply function.

The demand side of the model is motivated by the literature relating to the demand for durable goods. The fact that the demand for motor insurance is essentially a derived demand, being compulsory in the United Kingdom given that an individual owns a motor vehicle, results in a recursive model of the market that permits the identification of both demand and supply functions. The recursiveness results from specifying the demand function for motor vehicles as independent of the insurance premium, an assumption that is tested empirically and is not rejected by the data.

The broad implication of the theory—that there is a common moving average coefficient in both the demand and supply functions arising from the stock depreciation relationship for motor vehicles—is initially tested using time series models and is not rejected by the data. However, such models are inconsistent with a steady state solution, and so the econometric technique of embedding a so-called cointegrating relationship (long-term equilibrium) within a short-term dynamic (error correction) model is employed. The appropriate tests for nonstationarity of the data are

conducted, and a recursive cointegrated system is estimated. This long-term solution is then incorporated within an error correction model, which appears to be well specified based on the usual diagnostic tests.

The empirical work allows for structural changes in behavior as a result of the period of price regulation in the 1970s and the post-1974 oil price shock, and a significant effect is also detected in 1969 at the height of the spate of insurance company collapses in the United Kingdom. The estimated models also indicate considerable lags in adjusting behavior by both insurers and consumers.

References

- Baba, Y., D. F. Hendry, and R. M. Starr, 1992, The Demand for M1 in the USA: 1960-1988, *Review of Economic Studies*, 59: 25-61.
- Bar-Ilan, A. and A. S. Blinder, 1988, The Life Cycle Permanent-Income Model and Consumer Durables, *Annales d'Economie et de Statistique*, 9: 71-91.
- Bergstrom, A. R. and M. J. Chambers, 1990, Gaussian Estimation of a Continuous Time Model of Demand for Consumer Durable Goods with Applications to Demand in the United Kingdom, 1973-1984, in: A. R. Bergstrom, ed., *Continuous Time Econometric Modelling* (Oxford: Oxford University Press), 279-319.
- British Insurance Association, 1983, *BIA Facts and Figures 1983* (London: BIA).
- Central Statistical Office, 1987, *Economic Trends (Annual Supplement)*, (London: Her Majesty's Stationery Office).
- Fuller, W. A., 1976, *Introduction to Statistical Time Series* (New York: John Wiley).
- Hall, R. E., 1978, Stochastic Implications of the Life Cycle-Permanent Income Hypothesis: Theory and Evidence, *Journal of Political Economy*, 86: 971-987.
- Houthakker, H. S. and L. D. Taylor, 1966, *Consumer Demand in the United States: Analyses and Projections* (Cambridge, Mass.: Harvard University Press).
- Insurance Business Annual Reports*
- Johnston, J., 1984, *Econometric Methods*, Third Edition (London: McGraw-Hill).
- Mankiw, N. G., 1982, Hall's Consumption Hypothesis and Durable Goods, *Journal of Monetary Economics*, 10: 417-425.
- Rowe and Pitman, 1985, *Motor Insurance Annual Review 1985* (London: Rowe and Pitman).
- Sherden, W. A., 1984, An Analysis of the Determinants of the Demand for Automobile Insurance, *Journal of Risk and Insurance*, 51: 49-62.
- Stone, J. R. N. and D. A. Rowe, 1957, The Market Demand for Durable Goods, *Econometrica*, 25: 423-443.

United Kingdom, Department of Trade and Industry, 1984, *Business Monitor 1983* (London: Her Majesty's Stationery Office).

United Kingdom, Department of Trade and Industry, 1967-1984 (annually), *Insurance Business* (London: Her Majesty's Stationery Office).

Weiss, M. A., 1991, Efficiency in the Property-Liability Insurance Industry, *Journal of Risk and Insurance*, 58: 452-479.

Appendix

Data for new purchases of motor vehicles, average new car price, real interest rate, and real personal disposable income were obtained from *Economic Trends (Annual Supplement)*. Average motor insurance premium data were obtained from *British Insurance Association Facts and Figures*, *Insurance Business Annual Reports*, and *Rowe and Pitman Insurance Review*. All data reflect 1980 prices.

Variable	Maximum	Summary Statistics		
		Minimum	Mean	Standard Deviation
n_t	7.5745	5.5641	6.9580	0.5659
p_t	3.4936	3.0064	5.9976	9.8121
c_t	6.8884	5.9976	6.5122	0.2744
y_t	12.0173	9.8121	10.6047	0.7011
r_t	5.1900	-13.2900	0.2357	4.1131
Δn_t	0.3037	-0.2559	0.0579	0.1413
Δp_t	0.1828	-0.1112	-0.0032	0.0631
Δc_t	0.1596	-0.0749	0.0262	0.0581
Δy_t	0.2066	-0.0172	0.0649	0.0561
Δr_t	13.1000	8.6000	0.1547	4.9732

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