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A total energy demand model of Québec

Forecasting properties

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In this paper, we specify and estimate a two-levels integrated total energy demand model for the Province of Québec. The specification of the model has a close relationship with models currently used by Canadian public agencies to perform policy simulations and to make forecasts. The focus of the analysis is on forecasting. Two forecasting experiments are conducted while using within sample data. In the first experiment, we establish one-year forecasts, while in the second the model is solved recursively over the whole sample, which consists of annual data from 1962 to 1990. It is found that the model has good tracking properties and that most of the forecasting errors are random. The forecasting experiments show no significant structural defects of the estimated model as a forecasting tool.

Keywords: Energy models; Forecasting error analysis

The energy crises of the 1970s and the increasing concern with respect to the environment have generated a lasting interest for energy demand studies. Energy demand modeling has proceeded along several lines; the main differences are micro versus macro data; static versus dynamic specifications; single energy source versus substitution between several energy sources; and input versus output energy. For a survey of the studies up to the early 1980s, see Bohi [3] and Bohi and Zimmerman [4]. *The Energy Journal*, David Wood Memorial Issue [7] provides surveys of more recent works which emphasize short-run and long-run price and income elasticities, adjustment mechanisms and structural changes. Little attention is paid to the analysis of the forecasting properties of the estimated models. Operational energy demand models are used not only for policy simulation but also for forecasting. So estimated energy demand models should be assessed not only for their structural characteristics, but also for their forecasting properties.

The purpose of the present study is to bridge the gap at least partially. We estimate a total annual energy demand model by sector for the Province of Québec from a sample covering the period 1962 to 1990, and we analyze its forecasting properties. The specification of the statistical model borrows heavily from a model which is currently used for policy analysis and forecasting.[1] Our purpose is not to build the most precise forecasting model or to analyze the forecasting properties of the model which best satisfy the conditions derived from optimizing

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[1]See Sahi and Erdmann [14] for the Interfuel Substitution Demand Model (IFSDM) which is used by Natural Resources Canada. The model will be described more at length below.
[2]Chambers [6] presents the results of a study along these lines in a non-energy context.

behavior.[2] Rather we study the forecasting properties of a model which has been used over more than a decade to establish long-run energy demand forecasts in order to detect systematic biases. For a recent application, see Natural Resources Canada [11].

The first section describes the structure of the energy demand model. The next section presents the data and the estimation results including some comparisons with previous studies. The results of the forecasting error analysis, which is based on the mean squared error criterion and Theil [15] decomposition, are then presented. It is shown that the estimated model has good tracking properties within the sample both in the short run and in the long run and that most of the forecasting errors originate from the residual errors.

Model specification and links with previous studies

Energy demand modeling has proceeded along two lines either by focusing on a single energy source or by incorporating energy source substitution explicitly. Both approaches are used here to model total energy demand outside the transport sector in Québec: the first approach is applied to street lighting which relies exclusively on electricity and the second one is applied to the residential (R), commercial (C) and industrial (I) sectors. The sum of the four sectors yields non-transport total energy demand.

Total energy demand by sector with energy source substitution is modeled at two levels. At the first level the relative energy market shares, measured in thermal equivalence (TJ) held by each energy source, are made functions of the corresponding lagged energy market share and of relative prices of energy sources. The second level total demand, measured in terajoules (TJ), is made a function of lagged consumption, real energy price, real income and heating degree days, which is a measure of temperature. The aggregate energy price bridges the link between the two levels. A partial adjustment mechanism is applied at each level in order to account for the time dimension of the adjustment process.

More formally, the energy demand model by sector can be written in the following terms:

$$MS_{it} = f(MS_{it-1}, PO_t, PNG_t, PEL_t)$$
$$i = \text{fuel oil } (O), \text{ natural gas } (NG), \text{ electricity } (EL)^3 \qquad (1)$$

$$PE_t = \sum_i MS_{it} \times P_{it} \qquad (2)$$

$$TE_t = h(TE_{t-1}, PE_t/PI_t, IN_t, HDD_t) \qquad (3)$$

$$C_{it} = MS_{it} \times TE_t \qquad (4)$$

where

MS_{it}	=	market share of energy source i in year t
P_{it}	=	price of energy source i in year t
PE_t	=	price of total energy in year t
TE_t	=	total energy demand in terajoules in year t
PI_t	=	price index in year t
IN_t	=	real income in year t[4]
HDD_t	=	heating degree days in year t[5]
C_{it}	=	demand of energy source i in year t

Equations (1) to (4) form an integrated two-levels model of total energy demand and of its decomposition into separate energy sources. The set of functions (1) yields the energy market shares held by each energy source which are then used to obtain aggregate energy price (2). The latter is used in conjunction with real income, heating degree days and lagged total energy demand to determine total energy demand (3), which can be partitioned into its separate components (4). The above model provide a convenient formulation which can be easily used for policy simulation and for forecasting. Substitution possibilities among energy sources are incorporated explicitly into the set of functions (1) while the effects of aggregate energy price, income, and ambient temperature enter through function (3).

At the estimation stage, the function (3) is given a logarithmic functional form and the set of functions (1) are given a semilogarithmic functional form in terms of relative prices of energy sources. Since the set of energy market share functions (1) is a partition of total energy demand, some restrictions are imposed to ensure that the sum of the shares adds up to one:

(i) The energy market share functions are homogeneous of degree zero in the prices of energy sources;
(ii) the coefficient of the lagged energy market

[3]Coal products are also included in the industrial sector.

[4]Real personal disposable income per household is the real income variable in the residential sector. In the commercial and industrial sectors, it is the real gross domestic product (GDP) of the appropriate sector. Commercial real GDP is also used for street lighting.

[5]HDD_{t-1} also appears as an explanatory variable to capture only the short-run component of temperature changes.

share variable is the same for all functions;

(iii) the effect of the price of energy source i on energy market share j is the same as the effect of the price of energy source j on energy market share i;

(iv) the intercepts and the coefficient of the lagged variable add up to one.[6]

As they have been presented thus far the energy market share functions (1) bear a close relationship with energy expenditure shares that can be derived from a translog cost function except for one major difference: they are expressed in terms of thermal equivalence rather than expenditure shares. Since the early warnings of Turvey and Nobay [16] with respect to thermal versus relative price energy aggregation,[7] several energy demand studies have relied on relative energy prices to measure aggregate energy consumption. The use of thermal weights can introduce biases which are transmitted to estimated price and income elasticities. Nonetheless, some operational models of energy demand continue to make use of thermal equivalence to arrive at aggregate energy consumption.[8] There are three main reasons for the continuous use of aggregate measures of energy consumption which are based on thermal equivalence. These reasons are links with energy balance sheet, simplicity in terms of implementation, and ease of interpretation. Furthermore, government policies are quite often expressed and interpreted in terms of aggregate measure of energy consumption based on thermal equivalence.[9] So it is of interest to analyze the forecasting properties of energy demand models which make use of thermal equivalence to measure aggregate energy consumption and energy source substitution.

There is also an on-going debate about the appropriate use of input versus output energy. The latter takes into account the efficiency of the complementary equipment which is used in conjunction with energy to provide the required services, mostly in the form of heat, while the former measures energy quantities at the point of purchase. Both approaches coexist in the literature. Following the rather strong case made by Berndt and Watkins [2] in favor of the use of input energy, the latter approach is adopted in the present study.

The model introduced above has a close relationship with the Interfuel Substitution Demand Model (IFSDM), which is in use at Natural Resources Canada, with three significant differences. The first difference is that IFSDM relies on output energy measures which, according to Berndt and Watkins [2], result in a downward bias of estimates of energy demand price elasticities. The second difference is that IFSDM is applied to panel data composed of the 10 Canadian provinces from 1962 to 1977. Our study deals with Québec only. Finally, IFSDM makes use of samples which run from 1962 to 1977 only, while our sample period goes from 1962 to 1990. Statistics Canada changed its framework for energy statistics collection and reporting in the mid-1970s to ensure coherency with sectoral economic activities ie residential, commercial and industrial.

The IFSDM structure has already been adopted in another previous study by CERI [5] with a few changes. A more significant point in this respect is that CERI [5] used input energy measures as in the present study. Another point is that the sample period runs from 1962 to 1979 and, finally, there is no substitution possibility between electricity and fuels (oil products and natural gas) in the industial sector. The absence of substitution possibility is a very strong assumption to make for the Québec economy and it is not adopted in the present study.

Another study along the lines described above has been conducted by the National Energy Board (NEB) for its Energy Demand Model (EDM).[10] The latter model is used by the NEB to establish its long-term energy forecast for Canada. EDM is a static model. It is widely accepted that energy consumption requires complementary equipment and that, as a result, it adjusts slowly over time. Welsch [17] found that dynamic energy demand models have more desirable statistical properties than do static models.[11] Now let us turn to the empirical results.

Econometric results

The above model is estimated using annual time series data for the Province of Québec which ran from 1962 to 1990. Data have been gathered for separate energy sources ie electricity, natural gas and oil products in four sectors: residential, commerical, industrial, and street lighting. Aggregate energy consumption is obtained by adding up the energy sources which are measured in thermal units. Prices of energy sources are simple averages

[6] This is imposed by deleting one equation at the estimation stage. The coefficients of the equation which is left out are obtained in a residual fashion.

[7] See also Bernard and Cauchon [1] and Nguyen [12] for additional discussion of thermal versus relative price energy aggregation.

[8] See Sahi and Erdmann [14], Preece *et al* [13] and CERI [5].

[9] See Government of Québec [8] and National Resources Canada [11].

[10] See Preece *et al* [13].

[11] Chambers [6] also found dynamic models to present better forecasting performance than static ones.

Table 1 Total energy demand[a]

Explanatory variables	Residential	Commercial	Industrial	Street lighting
Constant	3.013	3.236	−0.037	1.090
	(3.67)	(6.07)	(−0.06)	(3.24)
Lagged dependent	0.593	0.444	0.545	0.874
	(6.90)	(3.76)	(5.50)	(11.91)
Real price of energy	−0.278	−0.327	−0.159	−0.153[b]
	(−4.35)	(−3.13)	(−3.46)	(−1.63)
Real disposable income per household	0.142	—	—	—
	(1.51)			
Commercial GDP	—	0.382	—	0.034
		(3.04)		(0.43)
Industrial GDP	—	—	0.604	—
			(4.39)	
Heating degree days	0.297	0.402	—	—
	(3.39)	(1.65)		
R^2	0.972	0.93	0.95	0.993
Durbin-h	0.45	0.97	2.29	0.86
Number of observations	28	28	28	28

[a] The t- statistics appear in parentheses.
[b] This is the real price of electricity.

obtained by dividing total expenditure value by total energy quantity.[12, 13]

The ordinary least squares (OLS) method is applied to function (3) which receives a log-linear form. The results appear in Table 1. Except for street lighting, which is a marginal sector using electricity only, the overall statistical results are quite satisfactory when they are assessed in terms of goodness of fit and statistical significance. All price and income coefficients display signs which are expected on *a priori* grounds. The lagged dependent variables have a high level of statistical significance and they indicate that a dynamic specification is more appropriate. Heating degree days, although statistically significant in the residential and commerical sectors, fail to reach significance in the industiral sector. The latter result is not too surprising when one considers the small role played by space heating in the industrial sector.

Various statistical tests have been performed to determine whether the assumptions underlying OLS application are satisfied by the data. In one test, auxiliary equations are estimated to measure the extent of multicollinearity among the explanatory variables. Multicollinearity turns out to be pervasive, as is usual with time series data, particularly when lagged dependent variables are in the model. Although multicollinearity leads to problems with respect to the precision of coefficient estimates of separate variables, it is not necessarily of concern in forecasting models.[14] We have also performed tests of heteroskedasticity of the variances of the error term through the application of a fairly general multiplicative form, as suggested by Harvey [10]. The results show no statistically significant heteroskedasticity of this type. Finally, the Durbin-h test is applied to determine whether autocorrelation of the first order is present in the estimated residuals. Except for the industrial sector, no autocorrelation of the first order is found to be statistically significant.

Zellner's seemingly unrelated regression procedure is applied to the set of energy market share functions (1) for which the results are shown in Table 2. The estimated coefficients of the lagged energy market shares are all relatively high ie greater than 0.90, thus indicating a slow adjustment process of market shares toward their equilibrium values after changes in the relative prices of energy sources. The relative prices of energy sources have the expected *a priori* signs in the residential and in the commercial sectors, although the cross-price effect is not statistically significant in the latter. The results show much more diversity in the industrial sector where the own price effects of electricity and coal are not statistically significant.

Table 3 displays the short-run and the long-run total energy demand price elasticities as they are measured in the present study and in some related works. In the present study, price elasticities are

[12] Sale taxes are included in the price of energy sources when they apply.
[13] The data appendix is available upon request.

[14] This is true as long as the multicollinearity which is present in the sample repeats itself over the forecast period.

Table 2 Market share equations[a]

Explanatory variables	Market shares Electricity	Oil	Coal
1 Residential sector			
Constant	0.084	−0.021	
	(4.75)	(−2.15)	—
Lagged dependent	0.930	0.930	
	(36.28)	(36.38)	—
Electricity price[b]	−0.046	0.046	
	(−3.95)	(4.44)	—
Oil price[b]	0.046	−0.052	
	(4.44)	(−4.31)	—
R^2	0.995	0.995	—
2 Commercial sector			
Constant	0.092	−0.018	
	(3.63)	(−1.09)	—
Lagged dependent	0.922	0.922	
	(25.53)	(25.53)	—
Electricity price[b]	−0.043	0.021	
	(−2.62)	(1.37)	—
Oil price[b]	0.021	−0.067	
	(1.37)	(−4.03)	—
R^2	0.964	0.984	—
3 Industrial sector			
Constant	0.030	−0.021	0.007
	(1.81)	(−1.29)	(1.01)
Lagged dependent	0.964	0.964	0.964
	(29.83)	(29.83)	(29.83)
Electricity price[b]	−0.020	0.044	−0.016
	(−1.62)	(3.28)	(−1.76)
Oil price[b]	0.044	−0.165	0.037
	(3.28)	(−4.97)	(2.03)
Coal price[b]	−0.016	0.037	0.004
	(−1.76)	(2.03)	(0.28)
R^2	0.929	0.957	0.937
Number of observations	28	28	28

[a] The t- statistics appear in parentheses.
[b] The price of the indicated energy source is relative to the price of natural gas.

found to be less than one except for street lighting in the long run. In general, our estimates are fairly close to those appearing in IFSDM and in CANREM. However, these are quite different from estimates of EDM.

Table 4 shows the short-run and the long-run total

Table 3 Total energy demand price elasticities

Sector	IFSDM[a]	CANREM[b]	EDM[c]	This study
Residential	−0.12	−0.12		−0.28
Short run			−0.39	
Long run	−0.40	−0.49		−0.68
Commercial	−0.42	−0.28		−0.33
Short run			−0.89	
Long run	−1.06	−0.62		−0.59
Industrial	−0.15	−0.07		−0.16
Short run			−0.68	
Long run	−0.48	−0.21		−0.35
Street lighting	—	−0.09		−0.15
Short run			0.0	
Long run	—	−0.71		−1.21

[a] IFSDM: Sahi and Erdmann [14].
[b] CANREM: CERI [5].
[c] EDM: Preece *et al* [13].

Table 4 Total energy demand income elasticities[a]

Sector	IFSDM	CANREM	EDM	This study
Residential	0.09	0.09		0.14
Short run			0.51	
Long run	0.34	0.35		0.35
Commercial	0.07	0.68		0.38
Short run			2.28	
Long run	0.18	1.34		0.69
Industrial	—	0.38		0.60
Short run			0.85	
Long run		1.23		1.33
Street lighting	—	0.09	—	0.03
Short run				
Long run		0.73		0.27

[a]For key to models see Table 3.

energy demand income elasticities. All income elasticities in the present study are less than one except in the industrial sector over the long run. If we set aside the EDM results, which are not directly comparable due to the static specification, the estimates for the residential sector are of the same order of magnitude as estimates in the three other studies. Unfortunately, this is not the case for the commercial and the industrial sectors.[15]

Forecasting error analysis

Energy demand models are usually compared on the basis of characteristics such as price and income elasticities, adjustment processes and structural changes. Little attention has been paid thus far to forecasting properties. The purpose of this section is to assess the accuracy of the forecasting precision of the model presented above. Such a model provides a convenient framework for predicting total energy demand and demand of the separate energy sources. The data inputs for forecasting over a predetermined horizon consist of standard macroeconomic variables and the prices of the energy sources for which information is commonly available.

Three types of errors are associated with the use of the energy demand forecasting model. One type of error deals with the data accuracy of the explanatory variable on the right-hand side of the equations. An error should be expected if the wrong information is introduced into the model. A second type of error is in the model structure itself. We must remember that model coefficients are estimates which are based on observations. The estimated coefficients cannot be expected to be identical to the true but unknown model. Finally, there are the random errors of the model which are set equal to their expected values which are assumed to be zero. In the forecasting experiments which are to be described below, we eliminate errors of the first type by inserting the actual values of the explanatory variables in the sample database, so that no forecasting error originates from this source. We will focus on model structure and on the estimated residual errors.

Two forecasting experiments, both using within sample data, are performed to highlight the forecasting properties of the total energy demand model of the Province of Québec.[16] The first experiment is a one-year period forecast. In this case the exogenous variables ie the macroeconomic variables and the energy source prices, together with the actual lagged dependent variables, are inserted into the estimated functions to arrive at the one-year forecast. The exercise is repeated every year over the sample period. This exercise is useful to assess the short-run forecasting accuracy of the estimated model. In the second experiment, the truly exogenous variables and the forecasted values of the lagged dependent variables are used as right-hand side variables in the estimated equations. The model is solved recursively over the whole sample period. This exercise allows for the assessment of the tracking properties of the model over the long run. Do the predicted series tend to err off the observed data path or do they tend to move back in line quickly toward the actual path? It must be kept in mind that since we rely on within the sample information, the analysis allows us

[15]In IFSDM, the long-run income elasticity in the industrial sector has been imposed to be one.

[16]A more appropriate test would have been to estimate the model over a restricted sample and to analyze the forecasting performance over the remaining sample. Since we rely on large sample results for some test statistics, the use of annual data does not provide a large enough sample for such an exercise.

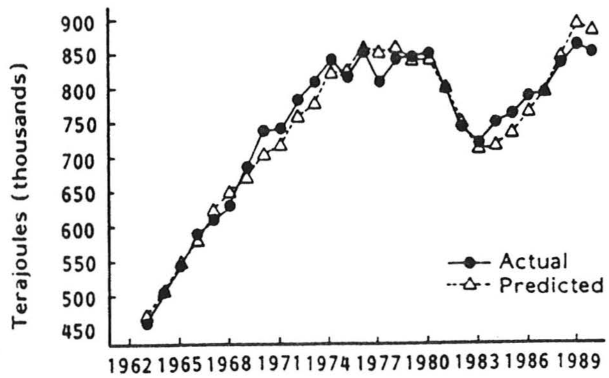

Figure 1 Québec total energy demand

to detect only the most crude forms of forecasting biases.

Figure 1 portrays the results of the second forecasting exercise. It can be seen that, except for the period 1970 to 1974, the tracking properties of the model are quite good. In particular, the model captures fairly accurately the turning points of the observed series. This is a strong performance in the light of the dramatic changes which occurred in the real price of energy in 1973, 1980 and 1985.

In order to gauge more precisely the results of the two forecasting experiments of the estimated model, we need an acceptable criterion. The most commonly used criterion in this respect is the mean square error:[17]

$$MSE = \sum_{t}^{N} (P_t - A_t)^2/N \tag{5}$$

where

P_t = predicted value in year t
A_t = actual value in year t

Theil [15] has shown that under the assumption of the mutal independence and of bivariate normality, the variance of MSE is

$$\text{var(MSE)} = \frac{2}{N}[1 - (Y^m)^2] \\ [E(P_t^2) + E(A_t^2) - 2E(P_t A_t)]^2 \tag{6}$$

where

$$Y^m = [E(P_t) - E(A_t)]^2 \\ /\left[E(P_t^2) + E(A_t^2) - 2E(P_t A_t)\right]$$

[17] For arguments in favor of the use of the *MSE*, see Granger and Newbold [9].

Theil [15] has also shown that the MSE can be decomposed into three parts:

$$MSE = \left(\bar{P} - \bar{A}\right)^2 + (S_p - rS_A)^2 + (1 - r^2)S_A^2 \tag{7}$$

where

S_p = the estimated standard error of P_t
S_A = the estimated standard error of A_t
r = the estimated simple correlation coefficient between P_t and A_t

The first part of the right-hand side of (7) is due to the difference between the mean of the observed series $\bar{A}$ and the mean of the predicted one $\bar{P}$. If this particular component of *MSE* were significant, then it would be easy to correct such an error by adjusting the level of the forecasting equation. The second term of (7) is an error associated with the fact that the slope of regression coefficient differs from one when A_t is regressed on P_t. This would indicate that P_t and A_t are not changing at the same pace and that significant variables may have been left out of the forecasting model which is used to calculate P_t. Finally, the third term is due to the estimated residual errors. The latter should not be expected to be zero unless P_t is deterministically equal to A_t.

If we divide both sides of Equation (7) by the *MSE* (5), we obtain:

$$1 = U^m + U^r + U^d \tag{8}$$

Granger and Newbold [9] have shown that, if the objective were to minimize the *MSE*, then in the ideal forecasting model, the first two components of the right-hand side of (8) would be zero and the only source of forecasting error would be the residual error. In an actual forecasting experiment, it is not usually so. Therefore it is of interest to test whether the first two components differ significantly from zero or not.

Theil [15] has established that, in large samples, the variances of the terms in (8) can be approximated by the following expressions:

$$\text{var}(U^m) = \frac{4}{N} Y^m \left(1 - \frac{Y^m}{2}\right)(1 - Y^m)^2 \tag{9}$$

$$\text{var}(U^r) = \frac{4}{N} Y^r \left[Y^d(1 - Y^r) + Y^m Y^r \left(1 - \frac{Y^m}{2}\right)\right] \tag{10}$$

$$\mathrm{var}(U^d) = \frac{4}{N}(Y^d)^2\left[1 - Y^d - \frac{(Y^m)^2}{2}\right] \qquad (11)$$

where

Y^r $= (\sigma_p - \rho\sigma_A)^2\,[E(P_t^2) + E(A_t^2) - 2E(P_t\,A_t)]$
Y^d $= (1 - \rho^2)\sigma_A^2\,[E(P_t^2) + E(A_t^2) - 2E(P_t\,A_t)]$
Y^m = as above
σ_p^2 and σ_A^2 = the variances of P_t and A_t
ρ = the simple correlation coefficient between P_t and A_t

By inserting sample moments in place of true moments, we can conduct large sample tests of significance.

Table 5 presents the results of the application of the above analytical framework to the two forecasting experiments which are obtained from the total energy demand model of the Province of Québec, ie the one-year solution and the recursive solution over the whole sample period. The results are presented for the four sectors and for the total economy. We can observe that, although the *MSE* are relatively small, their differences from zero are statistically significant. This can also be seen from the root mean squared error (RMSE), which can be readily compared to average growth rates of total energy demand. A second observation is that most of the forecasting errors come from the residual errors and the first two components of the *MSE* are not significantly different from zero. This implies that there are no obvious improvements that can be brought to the model.[18] A third observation is that there is little increase in the *MSE* when we move from the one year forecast to the recursive solution, thus indicating that the model has good tracking properties over the long run. Finally, the *MSE* for the total energy demand is smaller than the *MSE* of the sectoral components. Thus errors offset each other at the total level.

Conclusion

Most energy demand studies emphasize the structural characteristics of energy demand models, while little attention is paid to forecasting accuracy. The purpose of the paper is to correct in part this imbalance. We have specified an integrated two-levels energy demand model of the Province of Québec along the lines which are followed by some Canadian public agencies. Total energy is expressed in terms of input units, which are measured in thermal equivalent, and time series data are used to estimate the model coefficients. After estimation, the model is used to perform two within sample forecasting experiments: one short run and one long run. It is found that the model has good tracking properties within the sample despite the significant changes which occurred in the prices of energy sources and in energy consumption. Furthermore the decomposi-

[18] The possibility that another model would have smaller *MSE* by having smaller residual errors is not ruled out.

Table 5 Forecasting error analysis[a]

Sector	MSE	RMSE	U^m	U^r	U^d
Residential					
One year	0.00075	0.027	0.000	0.002	0.998
	(3.74)		(0.03)	(0.11)	(59.9)
Sample	0.00097	0.031	0.000	0.002	0.998
	(3.74)		(0.02)	(0.11)	(64.4)
Commercial					
One year	0.0044	0.066	0.001	0.001	0.998
	(3.74)		(0.09)	(0.07)	(59.7)
Sample	0.0076	0.087	0.002	0.009	0.989
	(3.74)		(0.12)	(0.25)	(25.0)
Industrial					
One year	0.0020	0.045	0.000	0.001	0.999
	(3.74)		(0.05)	(0.05)	(88.6)
Sample	0.0022	0.047	0.001	0.018	0.981
	(3.74)		(0.08)	(0.36)	(19.0)
Street lighting					
One year	0.0012	0.034	0.000	0.000	0.999
	(3.74)		(0.04)	(0.02)	(153.4)
Sample	0.0013	0.036	0.000	0.000	0.999
	(3.74)		(0.01)	(0.02)	(278.6)
Total					
One year	0.0005	0.022	0.001	0.019	0.980
	(3.74)		(0.07)	(0.37)	(19.1)
Sample	0.0006	0.025	0.002	0.013	0.985
	(3.74)		(0.12)	(0.31)	(21.6)

[a] The *t*-statistics appear in parentheses.

tion of the forecasting errors points to no significant structural defects. Since we rely on within the sample information, only the most crude forms of forecasting biases can be detected. Our study points to no significant biases of this nature. The use of annual data limits the analysis of more challenging aspects concerning structural stability and the nature of the adjustment process.

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