Residential Electricity Demand in Germany

by

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Abstract: I estimate residential demand for electricity in Germany with annual data for the period 1970 to 2006 and address the issue of cointegration with an ARDL error correction model. Among other things, results show that the variable 'unemployment' is significant in determining electricity demand in Germany. However, 'income per capita' remains the most important determinant for residential electricity demand in Germany. Moreover, the error correction coefficient suggests that about 32 percent of a shock is absorbed in the first year. Therefore, a rather fast, income driven, adjustment process seems to prevail with respect to residential electricity demand in Germany.

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1 Introduction

Estimates of residential demand for electricity have been neglected in Germany for more than a decade. To some extent this development may be explained by the deregulation process, which led to fundamental changes and induced researchers to focus on supply side issues rather than on the demand for electricity (e.g. see Pickhardt 2005; Niederprüm and Pickhardt 2002). Yet, with respect to the German electricity market, demand side issues should receive some attention for at least two reasons: (i) the long run need for an efficient use of primary and secondary energy makes it necessary to reconsider the demand for electricity with a view to identify potentials for savings in electricity consumption, (ii) the political agreement to replace all German nuclear power plants in the foreseeable future, combined with a growing share of renewables as a primary energy source for electricity generation may cause future load planning problems, so that demand side management (load management, smart metering, etc.) is bound to play an increasingly important role.

In general, two approaches for estimating residential electricity demand can be distinguished. The first uses aggregate data and the second microeconomic data at the household level (see Halicioglu 2007, for a brief overview). Following Erdogdu (2007), Narayan and Smyth (2005), Kamerschen and Porter (2004) and others, I use an aggregate or macro approach. In particular, I estimate the residential demand for electricity in Germany with annual data for the period 1973 to 2006 and address the issue of cointegration with an ARDL error correction model.

The paper proceeds as follows. In the next section, I introduce the ARDL error correction model. Section three provides the estimation results and a discussion of these results. The final section concludes.

2 The Model

Following Narayan and Smyth (2005, p. 469) and others, I specify the model of residential electricity demand as:

$$\ln(E/POP)_t = \alpha_0 + \alpha_1 \ln(Y_r/POP)_t + \alpha_2 \ln(PE_r/PG_r)_t + \alpha_3 \ln(Temp)_t + \alpha_4 \ln(Unemp)_t + \varepsilon_t \quad (1)$$

where *E/POP* denotes residential electricity consumption in MWh per capita, Y_r/POP is real GDP per capita, PE_r/PG_r is the ratio of the real price of residential electricity to the real price of natural gas, *Temp* denotes temperature measured in heating degree-days, *Unemp* is the unemployment rate, ε_t is the error term, *ln* denotes natural logarithms and *t* denotes time. Real (legal) GDP per capita is used as a proxy for legal residential income, which in turn is serving as an indicator of household spending on electrical appliances and electricity consuming activities. *Temp* proxies the impact of low temperatures on residential electricity consumption and *Unemp* proxies additional time spent at home, which in turn serves as a proxy for a more intensive use of electrical appliances at home. Therefore, Y_r/POP, *Temp* and *Unemp* are expected to be positively related to residential electricity consumption, whereas the relative price variable is expected to have a negative sign.

Because other approaches of cointegration are not robust for small samples (e.g. see Narayan and Smyth 2005, p. 468), I address the issue of cointegration by using the bounds testing procedure, within an autoregressive distributive lag (ARDL) framework, which was developed by Pesaran et al. (2001) and others. The ARDL error correction representation of (3) is:

$$\Delta \ln(E/POP)_t = \lambda_0 + [\lambda_1 (Trend)_t] + \lambda_2 \ln(E/POP)_{t-1} + \lambda_3 \ln(Y_r/POP)_{t-1} + \lambda_4 \ln(PE_r/PG_r)_{t-1}$$
$$+ \lambda_5 \ln(Temp)_{t-1} + \lambda_6 \ln(Unemp)_{t-1} + \Sigma\, \lambda_{7j}\, \Delta \ln(E/POP)_{t-j}$$
$$+ \Sigma\, \lambda_{8i}\, \Delta \ln(Y_r/POP)_{t-i} + \Sigma\, \lambda_{9i}\, \Delta \ln(PE_r/PG_r)_{t-i} + \lambda_{10}\, \Delta \ln(Temp)_t$$
$$+ \lambda_{11}\, \Delta \ln(Unemp)_t + u_t \qquad (2)$$

where Δ denotes first difference, i = 0,…, p, and j = 1, …, p, with p denoting the maximum number of lags. As I use annual data, the maximum number of lags in the ARDL is set equal to 2. Note, however, that the variables *Temp* and *Unemp* are set a priori to zero lags because these variables can influence residential electricity demand only in the present period. The data set consists of annual data from 1970 to 2006, where the first three years are reserved for the construction of lagged variables and first differences to ensure comparability of results for the main period under consideration, i.e., 1973 to 2006. However, for comparison and robustness checks, I also consider the two sub-periods 1975 to 2006 and 1977 to 2006.

To proceed, the null of no cointegration (H_0: $\lambda_2 = \lambda_3 = \lambda_4 = \lambda_5 = \lambda_6 = 0$) is tested against the alternative (H_1: $\lambda_2 \neq \lambda_3 \neq \lambda_4 \neq \lambda_5 \neq \lambda_6 \neq 0$) using a Wald or F-test. Given the small sample size, I use critical bounds values provided by Narayan (2005, pp. 1987-88). The null is rejected (accepted) if the calculated F-statistics are higher (lower) than the upper (lower) bounds value. If the F-statistics fall in between the bounds the test becomes inconclusive. As the results of the F-test depends on the lag length, I follow Pesaran et al. (2001, pp. 310-311) and first determine the appropriate lag length and whether a deterministic trend is required or not. Hence, I estimate (2) with and without a linear time trend and in each case for p = 0, 1, 2. Selection of the best performing lag length was made by minimizing the Schwarz Bayesian Criterion (SBC), because it can be shown that in small samples the SBC performs better than the Akaike Information Criterion (e.g. see Fatai et al. 2003, p. 89). Next I calculate the F-statistics and test for no residual serial correlation. Results are summarized in Table 1 and show that in each of the three periods the SBC suggests a lag length of zero, p = 0, and no trend. Moreover, in these three cases I cannot reject the null of no cointegration and, therefore, conclude that a long-run cointegration relationship among the variables is present in each model. Also, I cannot reject the null of no residual serial correlation.

Insert Table 1 about here

At this point it is worth noting that Bahmani-Oskooee and Ng (2002, p. 151) apply the bounds testing procedure in an alternative way by starting with the lowest number of lags and then stop once evidence of cointegration and no residual serial correlation is found for the first time. As can be seen from Table 1, this alternative also leads to the selection of zero lags, no trend, in each case. Hence, the outcome is identical with the results of the lag-order test based on Pesaran et al. (2001). Because the lag-order test and the Bahmani-Oskooee and Ng alternative both suggest zero lags, I directly get a parsimonious specification of (2) and can proceed with analyzing these estimations.[1] Results are summarized in Table 2.

Inspection of the three cases shown in Table 2 indicates that the model fits reasonably well in each period. All variables are highly significant and have the expected sign, except the relative price variable in the short-run. The latter might indicate that prices play a minor role in the short-run. The short-run model passes all standard diagnostic tests. Moreover, the long-run and short-run income elasticities and the long-run price elasticities of the three cases in Table 2 are in line with comparable studies (e.g. see Halicioglu 2007; Narayan and Smyth 2005), which further indicates that (2) is an appropriate model for residential electricity demand in Germany.

To rule out misspecifications due to parameter instability, I have applied the cumulative sum of recursive residuals (CUSUM) and the CUSUM of square (CUSUMSQ) tests to the three estimations of Table 2. Results (not yet displayed) indicate the absence of instability of the coefficients because the statistics are generally within the 5% critical bounds of parameter stability.

To search for other possible long-run relationships, I have applied an *F*-test to the 73-06 estimation with the following variables as dependent variables (in first differences and logarithm): Y_r/POP [(2.43)], PE_r/PG_r [(1.96)], *Temp* [(5.79)] and *Unemp* [(0.72)]. *F*-test results are given in brackets. Comparison with Table 1 shows that they are all well below the values which I obtain for the 73-06 specification (18.21). Moreover, according to the critical bounds values provided by Narayan (2005, pp. 1987-88), I cannot reject the null of no cointegration, except for the variable *Temp*. However, it is neither theoretically nor intuitively plausible that the variable *Temp* is explained by GDP per capita, unemployment, the relative price ratio or residential electricity consumption (see also Halicioglu 2007; Narayan and Smyth 2005). To this extent, the results indicate that there is no other plausible long-run relationship.

3 Discussion

Results displayed in Table 2 refer to the entire period under consideration 1973 to 2006 and, in addition, to two additional periods: 1975 to 2006 and 1977 to 2006. The impact of the oil-shock in 1973 is, therefore, fully incorporated in the first period, but only to a lesser extent in the second period and virtually not at all in the third period. Essentially, this is because none of the estimations is based on lagged values (see Table 1) and, thus, only one extra year is used for generating first differences. To this extent, the 1977 to 2006 period should yield the best performing SBC value and inspection of Table 2 shows that this is indeed the case.

Moreover, according to the adjusted R-squared, the residential electricity demand model in equation (2) explains about 90 percent of the variability in observed residential electricity consumption and each of the four model variables is significant at either the 1 percent or 5 percent level. Further inspection of Table 2 shows that residential electricity demand in Germany is predominantly determined by ‘income per capita’ and that the variable ‘temperature’ is the second most important determinant. In contrast, the variables ‘relative price ratio' and 'unemployment' both play a minor role. In fact, these observations are true for both the long and the short run model. Comparison of the coefficients with respect to the three periods shows that the relative importance of the variables does not change despite some fluctuations.

It is also worth noting that the variable 'relative price ratio' has the wrong sign in the short run. Hence, even if the relative price ratio increases, electricity consumption would still rise in the short run. This result indicates that German consumers may not consider price developments with respect to electricity or natural gas at the time they buy electrical appliances or engage in electricity consuming activities. In fact, this may be interpreted as further evidence for the finding that residential electricity consumption in Germany is mainly income driven. However, consumers do consider such price developments to some extent in the long run, as results in Table 2 show.

The finding that 'unemployment' is a significant determinant of residential electricity demand is rather new because no comparable study seems to consider this variable. According to Table 2 the relative importance of 'unemployment' compares to that of the 'relative price ratio' variable and is, therefore, not negligible. Essentially, this variable indicates that the stock of electrical appliances is more intensively used by unemployed people, because they spend more time at home. The latter is on the one hand directly due to the lack of employment (direct time effect), but on the other hand, also due to the need for cheep leisure activities (such as TV or DVD watching at home) because of a lower income (indirect time effect). It cannot be ruled out, however, that the finding is confined to welfare states of the European style, where unemployment not only fluctuates in terms of millions of people, but where millions of people are also permanently unemployed.

Inspection of Table 2 also shows that the short run model passes all relevant diagnostic tests at the five percent level. This notwithstanding, there might be some arch effects with respect to the third period (77-06) and heteroskedasticity may be present with respect to the second period (75-06). Finally, the error correction term, EC, has the expected negative sign and its significance may be taken as further evidence for cointegration. Moreover, the value of the error correction coefficient indicates that about 32 percent of a shock is absorbed in the first year after the shock, if the first period (73-06) is considered and even about 45 percent, if the third period (77-06) is considered. Together with the importance of the 'income per capita' variable this points to a rather fast and income driven adjustment process with respect to residential electricity demand in Germany.

To summarize, residential electricity demand in Germany is predominantly determined by the two variables 'income per capita' and 'temperature' and residential demand patterns adjust rather quickly within a few years.

4 Summary and Concluding Remarks

In this paper I have estimated residential electricity demand in Germany using the bounds testing method within an ARDL framework because this method yields more reliable results than other approaches to cointegration (see). Moreover, results with respect to the values of the coefficients are by and large in line with findings of comparable studies using the same estimation technique for other countries. Among other things, I find that 'unemployment' plays a significant role in determining residential electricity consumption in Germany. However, the latter is predominantly driven by 'income per capita' and 'temperature', i.e., cold weather during autumn and winter. In line with this finding, the variable 'relative price ratio' seems to play only a minor role in general, which is limited to the long run. Further, the adjustment process is comparatively fast and income driven.

With respect to policy implications, it is first of all worth noting that these findings help to explain why residential customers have shown only little reaction to lower electricity prices offered by alternative suppliers during the deregulation of the German electricity industry since 1998. To put this differently, the findings help to explain the low switching rates observed during the deregulation process. Also, with respect to future developments, the findings indicate that smart metering may have only limited success with respect to redesigning residential consumption patterns within certain periods, such as days, weeks or months, via price differentiation. In fact, electricity price changes may in general not have a substantial impact on consumption patterns. Therefore, electricity saving schemes should not be based on higher electricity prices, but rather on regulations that require manufacturers to implement power saving features in all electrical appliances.

Finally, due to global warming, ‘temperature’ is bound to loose in relative importance over time, so that in the foreseeable future ‘income per capita’ may dominate residential electricity demand in Germany even further.

Notes:

[1] Data was collected from the following sources: *Bundesbank*: consumer price index 1991-2005; *Christoffer (1995)*: Temperature 1971-1992, Table 2, row A3, p. 152; *IMF*: consumer price index 1960-1991; *OECD*: nominal and real GDP, GDP deflator; *Statistisches Bundesamt (Statistical Yearbook)*: population, residential electricity consumption 1971-2000; *Schiffer (1994-2007)*: residential electricity consumption 2001-2005, Temperature 1993-2005.

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Table 1: Model Selection Based on Lag Order Test and Bahmani-Oskooee/Ng

Lags	73-06	75-06	77-06
0	**SBC (-5.87) No Trend Wald (18.21)*** $\chi^2_{SC(1)}$ [0.46]**	**SBC (-5.86) No Trend Wald (13.38)*** $\chi^2_{SC(1)}$ [0.37]**	**SBC (-5.97) No Trend Wald (14.32)*** $\chi^2_{SC(1)}$ [0.14]**
0	SBC (-5.77) Trend Wald (12.98)*** $\chi^2_{SC(1)}$ [0.42]	SBC (-5.76) Trend Wald (10.48)*** $\chi^2_{SC(1)}$ [0.31]	SBC (-5.88) Trend Wald (12.19)*** $\chi^2_{SC(1)}$ [0.12]
1	SBC (-5.59) No Trend Wald (4.08)* $\chi^2_{SC(1)}$ [0.17]	SBC (-5.56) No Trend Wald (4.23)* $\chi^2_{SC(1)}$ [0.18]	SBC (-5.76) No Trend Wald (6.15)** $\chi^2_{SC(1)}$ [0.15]
1	SBC (-5.49) Trend Wald (3.64) $\chi^2_{SC(1)}$ [0.19]	SBC (-5.46) Trend Wald (3.72) $\chi^2_{SC(1)}$ [0.17]	SBC (-5.74) Trend Wald (6.39)** $\chi^2_{SC(1)}$ [0.06]
2	SBC (-5.60) No Trend Wald (4.78)* $\chi^2_{SC(1)}$ [0.13]	SBC (-5.57) No Trend Wald (4.55)* $\chi^2_{SC(1)}$ [0.01]	SBC (-5.64) No Trend Wald (4.99)** $\chi^2_{SC(1)}$ [0.05]
2	SBC (-5.50) Trend Wald (4.14) $\chi^2_{SC(1)}$ [0.17]	SBC (-5.47) Trend Wald (3.86) $\chi^2_{SC(1)}$ [0.03]	SBC (-5.54) Trend Wald (4.21) $\chi^2_{SC(1)}$ [0.02]

*Notes: SBC (·) denotes Schwarz Bayesian Criterion; Wald (·) denotes the F-statistics of the Wald test; ***, **, * denote significance at the 1, 5 and 10 percent level, respectively, for Narayan's (2005) critical bounds values; for example, Case III (unrestricted intercept and no trend, k=4, n=30): 1 per cent level,: 4.768-6.670, 5 percent level, 3.354-4.774, 10 percent level, 2.752-3.994; Case V (unrestricted intercept and unrestricted trend, k=4, n=30): 1 per cent level, 5,856-7.578, 5 per cent level, 4.184-5.540, 10 percent level, 3.430-4.624;* $\chi^2_{SC(1)}$ *denotes LM statistics for testing no residual serial correlation against order 1, with p-values in parenthesis.*

Table 2: Estimation Results Based on Table 1

Long-run ***Variable***	**73-06**	**75-06**	**77-06**
$\ln(Y_r/POP)_t$	0.624***	0.718***	0.709***
	(4.019)	(4.064)	(4.864)
$\ln(PE_r/PG_r)_t$	-0.118***	-0.10***	-0.07***
	(-3.960)	(-3.654)	(-3.354)
$\ln(Temp)_t$	0.387***	0.407***	0.340***
	(2.857)	(3.159)	(3.513)
$\ln(Unemp)_t$	0.080**	0.056*	0.056**
	(2.717)	(1.992)	(2.482)

*Notes: t-statistics given in parenthesis; ***, **, * denote significance at 1, 5 and 10 percent, respectively.*

Table 2: continued

Short-run **Variable**	**73-06**	**75-06**	**77-06**
Constant	-0.659	-1.130*	-1.147*
	(-1.267)	(-1.855)	(-1.974)
$\Delta\ln(Y_r/POP)_t$	0.408***	0.453***	0.491***
	(4.936)	(5.101)	(5.775)
$\Delta\ln(PE_r/PG_r)_t$	0.045**	0.051***	0.062***
	(2.542)	(2.837)	(3.493)
$\Delta\ln(Temp)_t$	0.240***	0.245***	0.244***
	(7.340)	(7.474)	(7.954)
$\Delta\ln(Unemp)_t$	0.039***	0.040***	0.062***
	(3.273)	(2.839)	(3.614)
EC_{t-1}	-0.319***	-0.357***	-0.446***
	(-5.991)	(-5.956)	(-6.449)
Adj. R^2	0.9039	0.8916	0.8858
s.e.	0.0090	0.0091	0.0085
SBC	-5.875	-5.863	-5.975
$\chi^2_{Norm}(2)$	2.62	0.69	0.98
	[0.27]	[0.71]	[0.61]
$\chi^2_{SC}(1)$	0.54	0.81	2.17
	[0.46]	[0.37]	[0.14]
$\chi^2_{ARCH}(1)$	0.15	0.523	3.16
	[0.70]	[0.47]	[0.08]
$\chi^2_{Hetero}(1)$	25.63	26.77	23.29
	[0.11]	[0.08]	[0.18]
$\chi^2_{RESET}(1)$	1.90	1.60	0.08
	[0.17]	[0.21]	[0.77]

Notes: EC denotes error correction term, Adj. R^2 denotes adjusted squared multiple correlation coefficient; s.e. is the standard error of the regression; SBC denotes Schwarz's Bayesian Information Criterion; $\chi^2_{Norm}(2)$, $\chi^2_{SC}(1)$, $\chi^2_{ARCH}(1)$, $\chi^2_{Hetero}(1)$ and $\chi^2_{RESET}(1)$ *denote chi-squared statistics to test for normality, no residual serial correlation, no autocorrelation in the error term, heteroskedasticity and no misspecification, respectively, with p-values in [·].*