Price freezes, durables and residential electricity demand. Evidence from the Greater Buenos Aires*

Ariel A. Casarin

Maria Eugenia Delfino†

Abstract

This paper examines the determinants of residential electricity demand in the Greater Buenos Aires between 1997 and 2006. During the second half of this period, residential tariffs remained nominally fixed, while an income boom boosted up the sales of durables. This study differs from previous works in that it explicitly considers the impact of the stock of air-conditioners on residential demand. The paper reports short- and long-run elasticities and examines the contribution of prices and durables to recent demand growth. Simulations illustrate the impact of prices and durables on future demand.

Keywords: Residential electricity; Durable goods; Error correction models; Short- and long-run elasticities

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† Both authors are at IAE Business School, Universidad Austral. Mariano Acosta s/n y Ruta Nac 8. Casilla de Correo 49. B1629WWA Pilar, Buenos Aires. Argentina. Tel: +54 2322 481000. Emails: ACasarin@iae.edu.ar; MDelfino@iae.edu.ar

1. Introduction

Electricity consumption has increased markedly during the last two decades, when growth in electricity demand outpaced growth in total energy use. Final electricity usage increased the most in developing nations, where industry reform – privatization and liberalization –, economic growth and rising personal incomes drove the growth in demand for electric power. The trend is expected to continue. In the mid-term, electricity is expected to be the fastest-growing form of end-use energy worldwide (IEA, 2009). Furthermore, social transformation in developing countries, which among other things leads to more people living in large urban concentrations, suggests that consumption growth will mostly originate in megacities, which will trigger the need to invest in clean, efficient infrastructures. It is not surprising then that those recent environmental concerns – related to pollution and scarcity – and industry reform have both renewed the interest in energy economic research.

Strategies to address energy concerns require an understanding of consumers' response to price changes. Hereof, recent work on residential electricity demand is basically of two types. On the one hand, some studies use micro data – typically residential energy consumption surveys – to examine more detailed responses at the household level. These studies, which refer exclusively to the US, focus on the heterogeneity of households' demand elasticities, their relation to appliance holdings and other household features (Bushnell and Mansur, 2005; Reiss and White, 2005; Davis, 2008). Unfortunately, micro energy data for other countries seldom exist, which therefore confine researchers to the use of aggregated time series that lead to general responses (Silk and Joutz, 1997; Holtedahl and Joutz, 2004 and Halicioglu, 2007). This limitation had made difficult the examination of the impact of durables on residential demand outside the US. This is unfortunate, given the recent evidence on the importance of incorporating appliance stock information into the analysis of electricity demand.

This paper partially fills this gap, as it uses time series data to examine the impact of durables on residential electricity demand in Buenos Aires, one of the 20 largest megacities in the world. To this end we are able to construct an aggregated series for the stock of air-conditioning equipment in the area that allows us to separate the impact of this appliance on electricity demand. Air-conditioners are important contributors to energy usage in their own right, being responsible for about one fourth of total residential electricity demand in the Greater Buenos Aires. Air conditioners are also appealing objects of study, given that the price reduction and substantial technological advancement they experienced over recent decades motivated a rapid diffusion of these appliances. What is more, while durable price and efficiency influence adoption, electricity prices are commonly believed to influence not only the timing of air-conditioning purchases but also the intensity of their use (Hausman, 1979; Rapson, 2008). The prolonged price freeze of residential electricity prices in Buenos Aires makes this case unique to examine the impact of durables on consumer demand.

The results of out study indicate that durables do matter for residential electricity demand. The estimated parameters of our model allow us to compute that the increase in the stock of air-conditioners explain, in relative terms, about 44% of the 25% increase in the per-customer electricity demand observed between 1997 and 2006. The regulatory tariff freeze accounts for 36% of the increase in demand, while the remaining 20% is due to the improvement in real income. The model also highlights the relevance of durables in predicting future demand. For instance, the model predicts that ignoring the growth in the stock of air-conditioners would lead in five years to an underestimate error of about 12% total current residential demand. Furthermore, the model also forecasts that the difference between lifting the price freeze and keeping 2006 real tariffs unchanged would equal, in five years time, to an increase in demand of about 15% of current residential demand.

The paper is organized into seven sections as follows. Section 2 describes briefly the residential electricity market in Buenos Aires and provides a brief account of the events that might have impacted consumption growth. Section 3 introduces the economic rationale of residential electricity demand using cointegration techniques. Section 4 describes the data sources and the variables used in the analysis. Section 5 examines the econometric results and the predictions of the demand model. In particular, this section reports the results of unit root and cointegration tests and the results of the long-run electricity demand. The section concludes with an evaluation of an estimated error correction model, which allows examining demand responses in the short-run. Section 5 contrasts our results to those of other previous studies. The last section derives policy implications and concludes.

2. Electricity demand in Buenos Aires

Argentina was one of the world's leading countries in terms of comprehensive electricity reform. The restructuring of the country's electricity sector began in 1991; the three stages of production (generation, transmission and distribution) of an industry wholly state and provincially owned were vertically disintegrated.[1,2] In only a few years, more than 80% of the generation (the national government retained hydro and nuclear power plants), all of the transmission and about 60% of the distribution sector (privatization was not entire because some provinces conserved their distribution firms) of a wholly state and provincially owned electricity industry was transferred into private

[1] The reform in electricity was one of the most significant of a more comprehensive program, which occurred against the important macroeconomic background of the Convertibility Plan, which in 1991 fixed the peso at par with the US dollar. The Convertibility Act established in May 1991 the parity of the austral (₳) - the denomination of the currency then - to the US dollar (at ₳10.000 per dollar). Shortly after, a new Act created the peso ($1 = ₳ 10,000) and the convertibility was reset at one peso per dollar.
[2] The large scale break up in generation and the separation of generation, transmission and distribution reflected the UK experience from 1990.

ownership. Generation became competitive, with transmission and distribution operating as regulated private monopolies.[3]

The state owned utilities in the Greater Buenos Aires, an area of about 14 million inhabitants, were at the forefront of the privatization process. Since 1992, this area is supplied by two distribution companies, EDENOR and EDESUR, which serve the north and south of the city and suburbs, respectively.[4] This area accounts for about 50% of total national electricity demand. Residential demand represents about 40% of these two firms' total demand. Electricity distribution in the Greater Buenos Aires area is regulated under concession contracts, with prices originally subject to review every 5 years, at which time the distribution tariffs for regulated customers were to be reset following assessment by the regulator under the principles of incentive regulation (CPI – X). Electricity tariffs for regulated customers (which include all residential consumers, small commercial and small industrial customers) can be adjusted quarterly to reflect changes in the seasonal energy price (every May and November) and in the price inflator (every February and August).

A salient regulatory feature is that tariffs were set in US dollars and then converted into argentine pesos at the official exchange rate established by the Convertibility Act. This occurred because the latter explicitly forbade the indexation of local currency contracts in Argentina. Therefore, the price index inflator of the price cap formula was a wholesale US price index, which disguised the nature of price caps, since the price inflator resulted neither in a domestic index nor of a consumers' variety type (Bernstein and Sappington, 1999). The major event affecting the sector has undoubtedly been the macro-economic crisis of 2002 (and the government reaction to it). In February 2002, when the peso was allowed to float freely, all prices within the sector were delinked to the US currency and fixed in nominal pesos. Wellhead fuel prices and regulated transmission and distribution charges were also converted to pesos at pre-devaluation exchange rates. Thereafter, residential electricity prices had remained nominally fixed, leading to a substantial real price decline.

The pesification of tariffs and the price freeze imposed following the devaluation distorted the relative prices of energy goods. Prior to the crisis, average residential tariffs were 8.9 cents per kWh, though by 2002 they reduced to just 2.5 US cents per kWh, the lowest in Latin America and extremely low by world standards, as compared to 9.8 cents a kWh in the US. Since the beginning of 2004, strong electricity demand stimulated by rapid economic growth and low relative energy prices has led to electricity supply shortages, especially during the summer, and emergency measures to reduce demand and increase domestic supply. By 2006, electricity prices in Buenos Aires were the lowest in the Southern Cone, as residential and industrial prices were

[3] See Delfino and Casarin (2003) and Pollit (2008) for reviews of Argentina's reforms in electricity.
[4] About 96% of Argentina's 38 million people have access to electricity, with connection rates of 70% in rural areas and 98% in urban areas. Half of the population lives in the Greater Buenos Aires area (the so called Gran Buenos Aires), a region that accounts for nearly half of the country's GDP. The national transmission system is focused on supplying power to this region.

both about 35% those of Brazil and Chile. Still, no proper regulatory review has yet been conducted following the macroeconomic crisis as prices were the subject of negotiation with the government. Yet, the price freeze went against a consumption boom, which between 2001 and 2006 has made durable equipment purchases to grow at about 9.6% per year, about twice the economy's growth rate.

3. Methodology

Residential electricity demand can be expressed as a function of economic determinants X, the stock of electricity-using appliances and the weather effect:

(1) $Q_t = f(PE_t, Y_t, PG_t, EA_t, T_t)$

where Q_t is the per-capita residential electricity consumption at time t, PE_t is the real price of electricity, Y_t is a proxy for real per capita income, PG_t is the average price of a substitute energy source (such as gas), EA_t is the stock of electricity using appliances and T is an indicator of weather intensity. Time-series demand studies usually assume that the demand specification of expression (1) can be parameterized using a Cobb-Douglas functional form. Writing (1) with such a functional form and taking logs gives:

(2) $\ln Q_t = a_0 + a_1 \ln PE_t + a_2 \ln Y_t + a_3 \ln PG_t + a_4 \ln EA_t + a_5 \ln T_t + w_t$

where a_0, a_1, a_2, a_3, a_4 and a_5 are parameters to be estimated and w_t is a stochastic residual term.[5] Note that the parameter a_1 to a_5 can also be interpreted as the elasticity of residential demand with respect to each independent variable.

The basic assumption underlying this approach is that the variables are stationary. However, Nelson and Plosser (1982) found that many economic series are not stationary but driven by stochastic trends (i.e. they are integrated of order one).[6] These trends in the data can lead to spurious correlations and to the misleading conclusion that a relationship exists between unrelated non-stationary series. Simple first differencing of the data will remove the non-stationarity problem, but at the cost of losing information regarding the long-run equilibrium relationships among the variables. Yet, if the non-stationary variables are cointegrated, then simple regression analysis will provide meaningful information about the long-run relationships among the variables.

Engle and Granger (1987) show that if all or a subset of variables are integrated of order one, there may exist a linear combination of the series that is stationary. This linear combination represents the long-run equilibrium relationship among the variables. In the case of electricity demand, the estimated residual from equation (2) represents the deviation between current and equilibrium levels. This can be written as follows:

[5] It is also possible to include lags of the variables to capture the dynamic aspects of electricity demand.
[6] If a series must be differenced d times before it becomes stationary, it contains d unit roots and is said to be integrated of order d [I(d)].

(3) $w_t = \ln Q_t - a_0 - a_1 \ln PE_t - a_2 \ln Y_t - a_3 \ln PG_t - a_4 \ln EA_t - a_5 \ln T_t$

Expression (3) suggests that cointegrated series can be represented in an error correction model (ECM). In the case of the electricity demand, the ECM can be expressed as follows:

(4) $\Delta \ln Q_t = b_1 \Delta \ln PE_t + b_2 \Delta \ln Y_t + b_3 \Delta \ln PG_t + b_4 \Delta \ln EA_t + b_5 \Delta \ln T_t + b_6 w_{t-1} + v_t$

where lags of the dependent and independent variables are included to capture additional short- and medium-term dynamics. The coefficients b_1 through b_5 represent short-run elasticities while the coefficient b_6 represents the speed of adjustment to equilibrium values.

Note that Engle and Granger's (1987) approach does not account for the potential endogeneity of the variables that enter the cointegration relation. This is a limitation, since the economic variables that are typically considered in the electricity demand specification (1), such as the price of substitutes and the stock of appliances, are likely to be endogenous. As a result, the estimation of electricity demand by means of a single equation would most probably produce simultaneity bias and therefore lead to unreliable estimates. This problem can be dealt with the help of the multivariate cointegration technique developed by Johansen and Joselius (1992), which is essentially useful to identify the presence of a stable and therefore, long – term equilibrium relationship, among the variables that enter the economic specification (1) above. We use this technique below to examine the contribution of potentially endogenous variables on residential electricity demand.

4. Data and Variables

The analysis of residential electricity demand uses monthly data from January 1997 to June 2006, which gives a total of 114 observations. The data come from several sources. Disaggregated data on monthly demand and total number of customers for each rate schedule and for each firm were provided by EDENOR.[7] Residential pre-tax rate schedules for these utilities were gathered from the regulator. All residential consumers in Buenos Aires pay a fixed charge and a single unit price, though these rates vary in line with consumption. During the sample period, households with an average maximum monthly consumption below 150 kWh paid a lower standing charge but a higher marginal price (rate schedule T1R1) than those consuming above that threshold (rate schedule T1R2).[8] Statistical evidence indicates that households seldom switch between rate schedules, which allowed us to construct a series of post-tax marginal

[7] EDENOR and EDESUR interchanged residential consumption data during this period. The sum of both firms' residential demand gives total residential demand in the Greater Buenos Aires area. The data were adjusted to correct for differences in billing periods across these two firms.

[8] The two rate schedules yield a similar expenditure (3% difference) when consumption is 150KWh.

prices for each rate schedule using detailed local and national tax rates levied on electricity consumption. We then constructed a weighted average of these two price series using disaggregated consumption data at the rate schedule level for each of the two firms. We then adjusted this price series using the Consumer Price Index (CPI) provided by the National Statistics Office (INDEC). This is the marginal price of electricity we use in our empirical analysis.

We also develop an income variable using the average gross wage monthly series per district available from the Integrated System of Pensions (SIJP), which are gathered from the Ministry of Economics. We then assembled the series for each district into a single one for the Greater Buenos Aires using each district's population as weights. This series was then deflated with the CPI. We also computed several gas price series to account for the impact of substitute energy goods. We constructed three gas price series.[9] One consists of the unit price of piped gas, which is available from the gas regulator (ENARGAS). We assembled this series combining the (single) unit price of piped gas of the two distributors – METROGAS y GAS BAN – servicing the Greater Buenos Aires area using number of customers as weights. The other gas variable consists of a series for the price of bottled gas, which we obtained after commissioning a special work to INDEC. The last series result of a combination of the other two, using usage rates as weights. These rates were obtained from the 2001 National Census, available from INDEC.

The stock of air-conditioning equipment was computed using the perpetual inventory method, which assumes that the capital stock evolve according (in discrete time) to $K_t = I_t + (1- \delta) K_{t-1}$, where K_t is the stock of air-conditioners at time t, I_t captures additions made at time t and δ_i is the geometric economic rate of depreciation. This approach to computing capital stocks requires an estimate of initial capital stock (or benchmark), a series of investment data and estimates of a geometric rate of depreciation. The initial stock of equipment was estimated using appliance holding data for Buenos Aires' residents as available from the National Household Expenditure Survey (ENGH) carried out between March 1996 and March 1997 by INDEC.[10] This survey indicates if the household owns air-conditioning equipment, but it does not question about the number of units it has. We therefore computed three stock series using alternative initial benchmark values K_0: one series assumes that each household that in 1996 reported having air-conditioning equipment had on average 1.25 units, the second assumes that it

[9] The Argentinean residential gas market presents the particularity that all households use gas, though a proportion of them choose not to connect to the piped gas grid but to use bottled (LPG) gas instead. Residential piped gas is provided by regional bundled distribution and supply firms, whose tariffs are established by a national regulator (ENARGAS). Tariffs structures across these firms are alike, but tariff levels differ because of differences in firms' operating costs. Bottled gas has a different price regime, with prices being determined in (imperfect) competitive markets with cross-border arbitrage.

[10] The ENGH is the only household expenditure survey administered in Argentina during the 1990s

had 1.5 units, and the third 1.75 units, on average. We use all three series in the econometric estimation.[11]

Additions of air-conditioning equipment result from the sum of national production and net imports. These two annual series were available from INDEC's Industrial Products Statists (EPI) report and international trade data at the product level, respectively.[12] We developed an estimate of depreciation rates using a lifetime of 13.75 years, which results in a 6.875% geometric depreciation rate.[13] Finally, we transform these annual series into monthly series, using the seasonality pattern reflected in the monthly series of air-conditioners sales (in pesos) provided in INDEC's Survey of Sales in Shops of Electrical Appliance and Household Goods. Table 1 provides summary statistics of the variables used in the analysis.

Table 1
Data Summary Statistics

Variable	Symbol	Mean	Std.Dev.	Min	Max
Residential electricity consumption	Q	207.2	15.9	175.9	253.5
Price of residential electricity	P	0.069	0.015	0.045	0.090
Income per capita	Y	0.954	0.092	0.780	1.118
Price of pipped gas	PG_{pipped}	0.163	0.030	0.106	0.202
Price of bottled gas	PG_{bottled}	12.73	2.87	9.14	17.58
Price of gas (average)	PG	0.928	0.106	0.688	1.086
Stock of air conditioners (1.25 per household)	EA (1.25)	749,237	209,700	396,962	1,148,170
Stock of air conditioners (1.50 per household)	EA (1.50)	806,461	198,755	474,482	1,188,237
Stock of air conditioners (1.75 per household)	EA (1.75)	863,685	187,853	552,001	1,228,304
Cooling degree days	CDD	70.05	73.25	0.00	254.90
Heating degree days	HDD	69.72	73.33	0.00	273.60

5. Empirical Results

This section reports the results of our empirical estimates. The first step involves examining the time series properties of the data. Therefore, the first subsection describes the results from testing for the order of integration of the model variables. We then test for potential cointegration relationships and examine the estimated long-run model. In this subsection we analyze the structural shift that followed the price freeze of 2002. The final subsection reports the results from the error correction model.

[11] Still, capital stock series are almost invariant to the initial capital stock with a long time series of investment data. For example, holding the values for additions and depreciations unchanged, the final capital stock estimates under the two scenarios differ by 6% only.
[12] We consider products under Mercosur's Common Trade Codes 84151010; 84158110; 84158210; 84158300. These codes represent equipments aimed at household and small commercial uses.
[13] Hausman (1979) calculates the mean lifetime of air-conditioning equipment to be 9.94 years, with a median lifetime of 8.49 years. The 25th percentile is 4.61 years, while the 75th percentile is 13.74 years. We use the latter figure, as technological advances had most probably extended the lifetime of durables.

a. Unit roots tests

The first step of the empirical analysis involves verifying the order of integration of the series, as cointegration tests are only valid if the variables have the same degree of integration. We use several tests to examine the order of integration of the series. We first apply the ADF test developed by Dickey and Fuller (1979, 1981). This test is derived from the estimation of the following regression for each of the z_t variables used in the analysis:

$$(5) \qquad \Delta z_t = \alpha_0 + \alpha_1 t + \alpha_2 z_{t-1} + \sum_{i=1}^{k} \gamma_i \Delta z_{t-i} + u_t$$

where t=1,…,T is a time trend term. The lagged differences of z_t are added to correct for serial correlation in the residuals. The lag length *k* is selected using the method proposed by Ng and Perron (1995). We then use the PP test due to Phillips (1987), Perron (1988) and Phillips and Perron (1988). This test is derived from estimation of (5) without the lagged differences of z_t, as this test corrects for any serial correlation in the errors by directly modifying the t statistics of the α coefficients. For both tests the null hypothesis of a unit root (H_0: α_2=0) is tested against the alternative of stationarity. Next, the KPSS test of Kwiatkowski et al. (1992) is derived from the estimation of the following model:

$$(6) \qquad z_t = \alpha_0 + \alpha_1 t + \mu_t + u_t$$

where $\mu_t = \mu_{t-1} + \varepsilon_t$ and $\varepsilon_t \sim WN(0,\sigma_\varepsilon^2)$. The KPSS statistic is the Lagrange Multiplier for testing the null of stationarity (H_0: σ_ε^2=0) against the alternative of a unit root. This test reverses the null and alternative hypotheses. We estimate two different forms of (5) and (6) are estimated, where each differs in whether the time trend term is included or not.

Figures 1(a) through 1(h) show time-series plots of logs of the variables examined. The clear trend-like shapes of the variables LQ, LY, LPE, LPG and LAC over the whole period indicates that the series appear to be non-stationary. In contrast, Figure 1(f) suggests that the variables HDD and CDD are stationary. This is tested using the ADF, PP and KPSS tests, whose results are displayed in Table 2. The first rows present the test results for the order of integration in the levels of the variables, while the last rows report the test results for testing the degree of integration of the first difference of the series. The column headed τ_τ (τ_μ) presents the t statistics for testing the significance of α_2 (i.e. null hypothesis of a unit root) when a time trend is included (not included) in (5). Similarly, the column headed η_τ (η_μ) reports the KPSS statistic for testing σ_ε^2=0 (i.e. null hypothesis of stationarity) when a time trend is included (not included) in (6).

Figure 1

Figure 1(a). Per-capita electricity consumption

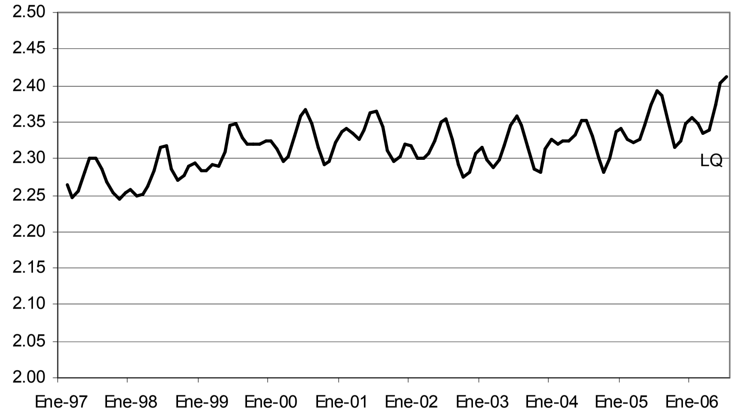


Figure 1(b). Real electricity prices

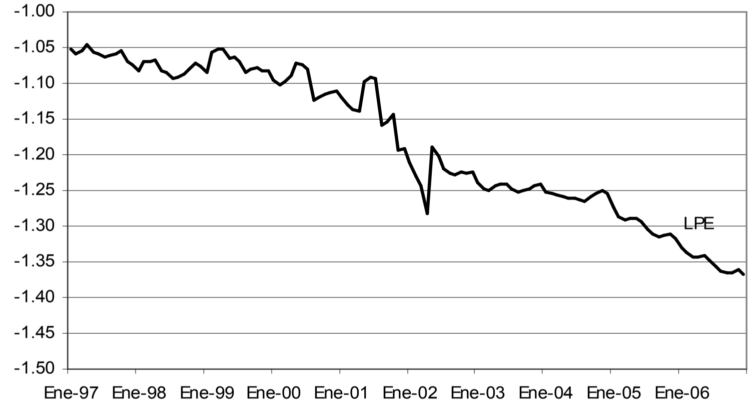


Figure 1(c). Per-capital real income

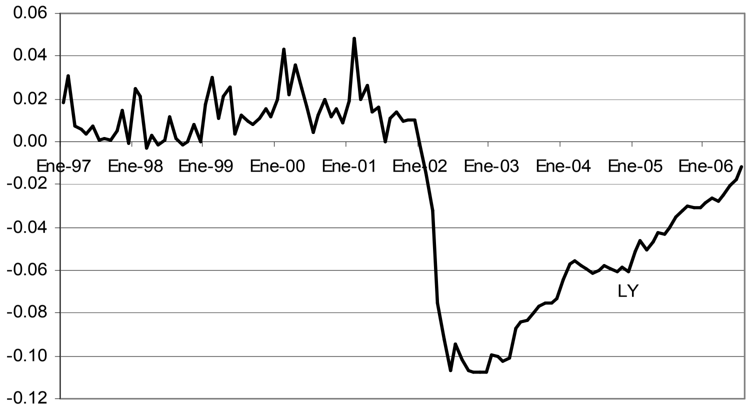


Figure 1(d). Real gas prices

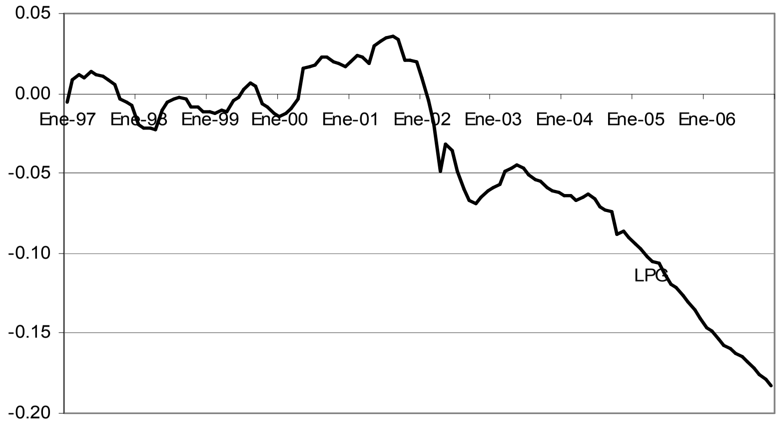


Figure 1 (Cont.)

Figure 1(e). Stock of air conditioners (EA1.25)

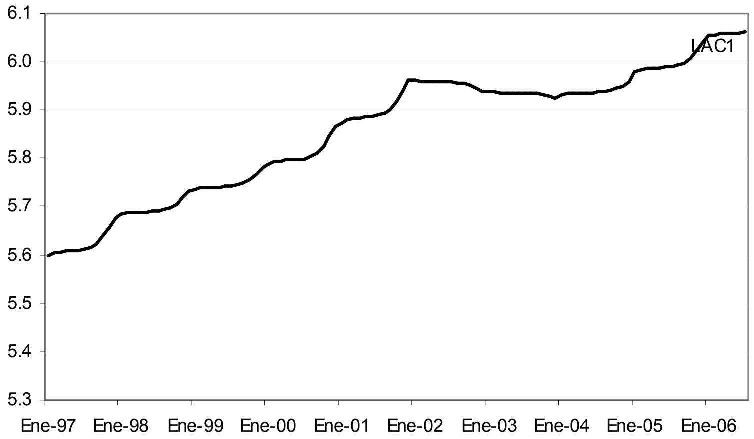


Figure 1(f). Stock of air conditioners (EA 1.75)

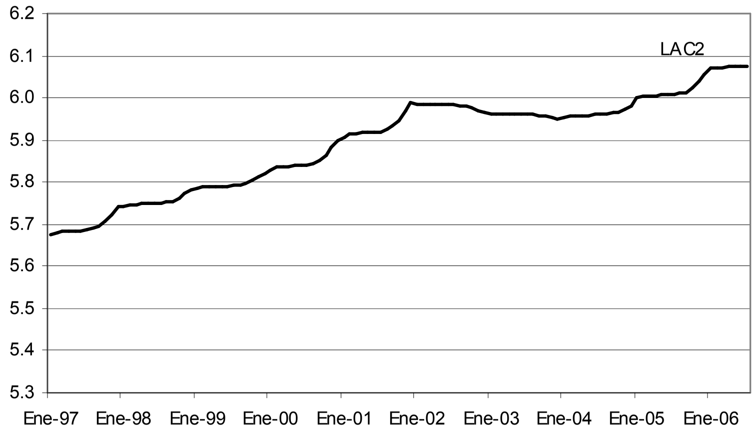


Figure 1(g). Cooling-degree days

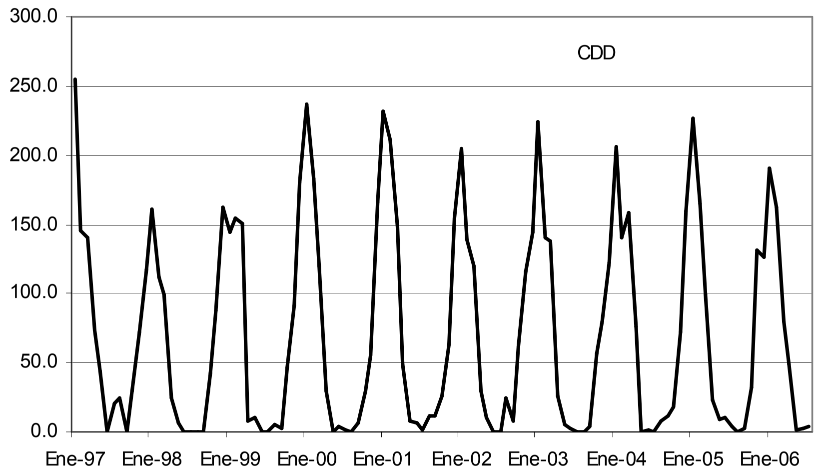


Figure 1(h). Heating-degree days

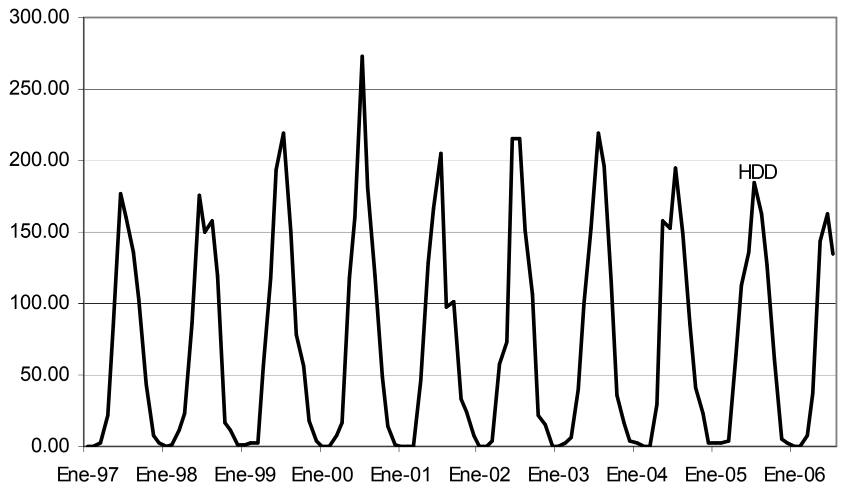


Table 2
Tests of unit roots – ADF, PP and KPSS

Variable	p	ADF τ_τ	ADF τ_μ	PP τ_τ	PP τ_μ	KPSS η_τ l=1	KPSS η_τ l=4	KPSS η_μ l=1	KPSS η_μ l=4
LQ	11	-1.91	-1.62	-2.60	-1.71	0.18 **	0.15 *	1.30 ***	0.89 ***
LPE	12	-2.23	-0.62	-3.14	-0.42	0.24 ***	0.15 *	2.31 ***	1.34 ***
LPG	12	-1.86	-0.24	-1.18	-0.95	0.46 ***	0.28 ***	1.78 ***	1.05 ***
LY	12	-2.36	-2.27	-1.60	-1.66	0.24 ***	0.14 *	1.24 ***	0.73 **
LAC	12	-3.18 *	-0.55	-1.62	-1.32	0.43 ***	0.26 ***	5.33 ***	2.21 ***
CDD	12	-2.58	-2.05	-6.40 ***	-6.16 ***	0.03	0.02	0.08	0.06
HDD		-2.18	-2.20	-4.99 ***	-5.06 ***	0.04	0.03	0.04	0.03
D.LQ	11	-3.46 **	-3.46 **	-5.95 ***	-6.04 ***	0.05	0.06	0.06	0.08
D.LPE	10	-5.01 ***	-4.77 ***	-13.73 ***	-13.44 ***	0.05	0.05	0.11	0.12
D.LPG	10	-3.40 *	-2.80 *	-8.59 ***	-8.51 ***	0.05	0.05	0.42 *	0.37 *
D.LY	10	-2.78	-2.74 *	-11.94 ***	-11.91 ***	0.11	0.10	0.16	0.15
D.LAC	11	-3.26 *	-3.13 **	-3.46 **	-3.46 **	0.13 *	0.09	0.29	0.18
D.LCDD	11	-7.98 ***	-8.01 ***	-26.83 ***	-26.96 ***	0.01	0.02	0.01	0.02
D.LHDD	11	-7.80 ***	-7.85 ***	-16.79 ***	-16.95 ***	0.02	0.03	0.03	0.04
Critical values									
1% (***)		-4.04	-3.49	-4.04	-3.49	0.22		0.74	
5% (**)		-3.45	-2.89	-3.45	-2.89	0.18		0.46	
10%(*)		-3.15	-2.58	-3.15	-2.58	0.12		0.35	

Notes: The null hypothesis under the ADF and PP tests is that of a unit root against the alternative of stationarity. The KPSS test reverses the null and the alternative hypothesis. The critical values for the ADF and PP tests are calculated using the statistics reported in Dickey and Fuller (1981). The critical values for the KPSS tests are from Table 1 of Kwiatkowski et al. (1992). ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

Results of the ADF statistic suggest that the variables LQ, LPE, LPG, LY and LAC are integrated of order one I(1) but that the weather variable is integrated of order zero I(0).[14] The PP test reveals that the variables LCDD and LHDD are stationary I(0) while all other variables are integrated of order one I(1). Finally, the KPSS statistic for lag-truncation parameters four and eight (l=4 and l=8) imply that the weather series appear to be a I(0) process whereas all other series are I(1). The combined results of these tests suggest that the variables LQ, LPE, LPG, LY and LAC appear to be I(1) processes, while the LCDD and LHDD series is stationary.

Although the previous tests suggest the presence of unit roots, Figures 1 (a) to (e) seem to suggest the presence of a shift for all series at the beginning of 2002, which coincides with the devaluation of the Argentine peso in January 2002. Zivot and Andrews (1992) show

[14] Results are similar for the three alternative air-conditioners series, EA (1.25) through EA (1.75).

that the presence of a structural break may lead traditional unit root tests to fail to reject the null of unit roots. In addition, they emphasize that the breakpoint should be estimated rather then fixed (Perron, 1990), even if structural breaks are caused by exogenous events.

Therefore, we also use the Zivot-Andrews (ZA) test because it modifies the ADF test to allow for structural breaks in the time series examined. This test allows us to verify the results of the ADF, PP and KPSS tests. The ZA test is derived from the estimation of the following regression:

$$\Delta z_t = \alpha_0 + \alpha_1 t + \alpha_2 z_{t-1} + \delta DU_t + \theta DT_t + \sum_{i=1}^{p} \gamma_i \Delta z_{t-i} + u_t \tag{7}$$

where DU_t is a dummy variable for a mean shift occurring at each possible break-date (TB), and DT_t is a corresponding trend shift variable. Two different forms of (7) are estimated, each one differing in whether the δDU_t term or the θDT_t term is included. The null hypothesis is $\alpha_2 = 0$, which implies that the series z_t contains a unit root with a drift that excludes any structural break, while the alternative hypothesis implies that the series is a trend-stationary process with a one-time break occurring at an unknown point in time. The ZA method considers every point in the series as a potential break-date (TB) and runs a regression for every possible break-date sequentially. From amongst all possible break-points (TB), the procedure selects as its choice of break-date (TB) the one that minimizes the one-sided t statistic for testing $\hat{\alpha}_2=1$.[15] We use the ZA test to verify the order of integration of the I(1) series LQ, LPE, LY, LPG and LAC. Table 3 presents the t statistics estimated from a break in intercept and a shift in the trend.

The results suggest that all variables but LPE do not appear to be stationary around a broken trend or a shift in the mean and that the first differences of these series follow a I(0) process. These results seem to confirm that the series LQ, LPG, LY and LAC are integrated of order one. However, the test suggests that the LPE variable seem to be stationary around a shift in the mean. Because the results for LPE were not conclusive, we went further and used the test proposed by Clemente et al. (1988) that allows for breaks in the series. In this case, the test statistic for LPE with one (two) break (s) is -0.787 (-2.604), which is greater than the 5% critical value of -3.56 (-5.49). The results from this test suggest that the series LPE is integrated of order one.

[15] The presence of the end sample points cause the asymptotic distribution of the statistic to diverge towards infinity. Therefore, some region must be chosen to exclude the sample end points. Zivot and Andrews (1992) suggest the 'trimming region' be specified at (0.15T, 0.85T). Our estimations follow this approach.

Table 3
Zivot-Andrews test

Variable	Intercept			Trend		
	t		Period	t		Period
LQ	-4.79		2002:07	-3.91		1999:07
LPE	-5.24	**	2001:08	-4.08		1999:04
LPG	-3.03		2000:01	-3.90		2001:04
LY	-4.69		2002:01	-2.51		2003:08
LAC	-3.57		2002:10	-2.43		2001:01
D.LQ	-8.77	***	2001:07	-8.46	***	2002:10
D.LPE	-8.66	***	2002:05	-7.42	***	2001:12
D.LPG	-9.06	***	2001:08	-8.56	***	1999:05
D.LY	-6.873	***	2001:12	-5.92	***	2003:10
D.LAC	-6.81	***	2002:01	-5.72	***	2003:11
Critical values						
1% (***)	-5.43			-4.93		
5% (**)	-4.80			-4.42		

Notes: The null hypothesis is that of a unit root with a drift that excludes any structural break while the alternative is that of trend-stationarity with a one-time break. Critical values are those reported in Table 4 of Zivot and Andrews (1992). ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.

b. Cointegration tests and long-run demand estimation

The results from the previous section indicate that the variables entering the demand function are non-stationary. Therefore, we next examine the presence of cointegration relationships among the variables. The most common approach to test for cointegration is the single equation method developed by Engle and Granger (1987). This approach, however, has several disadvantages. The major problem is that there can be more than one cointegration relationship among the variables when the model includes more than two. The adoption of a single equation approach is then inefficient as only one linear combination of these vectors (i.e. long-run relationship) can be obtained. Moreover, even if there is only one cointegration relationship, the estimation of a single equation is potentially inefficient. This results from the fact that, unless all the right-hand-side variables in the cointegration vector are weakly exogenous, information is lost by not estimating a system which allows each endogenous variable to appear on the left-hand side of the estimated equations in a multivariate model.

These reasons lead us to test for cointegration using the multivariate approach developed by Johansen and Joselius (1992). All the variables are thus modeled as a vector autoregression (VAR) involving up to k-lags for each variable as follows:

(8) $$z_t = A_1 z_{t-1} + \ldots + A_k z_{t-k} + \varepsilon_t$$

where z_t is a matrix of endogenous variables, A_i are coefficient matrices and ε_t is a matrix of random disturbances assumed to be approximately normally distributed. The system is in reduced form with each variable in z_t regressed, only, on lagged values of both itself and all the other variables in the system. The system in levels (8) is reformulated into a vector error correction (VECM) that contains information on both the short- and long-run adjustments to changes in z_t, as follows:

(9) $$\Delta z_t = \Gamma_1 \Delta z_{t-1} + \ldots + \Gamma_{k-1} \Delta z_{t-k+1} + \Pi z_{t-k} + \Psi D_t + \varepsilon_t$$

where D_t is a matrix of I(0) variables that are both weakly exogenous and insignificant in the long-run cointegration relationship.[16] The matrix Π can be partitioned as $\Pi=\alpha\beta'$ where α is the matrix of speed adjustment coefficients and β is the matrix of cointegrating vectors or long-run coefficients. Since the variables in z_t are non-stationary I(1), then Πz_{t-k} must be stationary for $\varepsilon_t \sim I(0)$ to be white noise. This occurs when the matrix Π has reduced rank; there are $r \leq (n-1)$ cointegration vectors where n is the number of endogenous variables. Hence, testing for cointegration amounts to considering the rank of Π, which requires finding the number of r linearly independent columns in Π. The Johansen maximum likelihood approach is used to test for cointegration and to find maximum likelihood estimates of β.

The VAR is estimated over the period 1997:01-2006:06 including 9 lags of each variable. The appropriate lag length for the VAR is determined using several diagnostic tests of the residuals for various lags lengths.[17] Given the monthly frequency of the data, an initial version of the VAR was estimated with 12 lags, but the diagnostic tests suggested an optimum lag length of 9 lags. Each equation of the VAR system passed Wald tests for lag exclusion, Lagrange Multiplier tests for serial correlation and normality tests The Wald lag exclusion test indicates that twelfth-, eleventh- and tenth-period lags are not significant in at least one of the equations of the system. The Lagrange multiplier suggests the absence of serial correlation. Residuals appear to be normally distributed in LQ and LY but non-normally in LP and LAC equations.

The endogenous variables entering the VAR are LQ, LPE, LY and LAC. The variable LPG is not included in the model as results proved inconsistent when it was considered, probably because it is highly correlated with the electricity price. In addition, we never found a specification that made this variable statistically significant. The contemporaneous value of LCDD and LHDD, a constant and a dummy variable for the first semester of 2002

[16] The variables in D_t are often included to take account of short-run shocks to the system.
[17] Hypothesis tests with respect to the residuals of the model are valid since these are stationary I(0) on the presumption that there are cointegration relationships in the data (Harris p.121 fn.16).

(D2002:I), to take account of the shift caused by the peso devaluation, are also included in the system as weakly exogenous variables. Table 4 reports the results from the Johansen cointegration test.

Table 4
Johansen Cointegration Test

Cointegration analysis						Standardized eigenvectors β'			
Null Hipótesis	Eigenvalue	Maximal Eigenvalue	Critical value	Trace Statistic	Critical value	LQ	LPE	LY	LAC
r=0	0.303	37.61	27.07	57.86	47.21	1	0.21	-1.31	-0.22
r≤1	0.125	13.89	20.97	20.25	29.68	-7.85	1	2.85	2.88
r≤2	0.053	5.69	14.07	6.36	15.41	-3.28	-0.53	1	0.21
r≤3	0.006	0.67	3.76	0.67	3.76	-0.85	2.20	-2.02	1

Notes: r indicates the number of cointegrating relationships. The 95% critical values are taken from Osterwald-Lenum (1992).

The results from the maximum eigenvalue and trace statistic provide evidence to reject the null hypothesis of zero cointegrating vectors in favor of one cointegrating vector at the 5% level. We also test whether all variables in the cointegrating vector are statistically significant. Table 5 presents the Likelihood Ratio tests (LR) and Wald tests of restrictions on the variables entering the cointegrating vector. The results suggest that all four variables enter statistically significant into the cointegrating vector. The LR tests for weak exogeneity, which are also presented in Table 5, show that for the variables LQ, LPE, LY and LAC the null hypothesis of weak exogeneity is rejected at the 10% or lower significance level.

Table 5
Long-run Hypothesis Tests

Variable	Test of restrictions that variable z_t does not enter the cointegration vector		LR test of weak exogeneity
	LR Test	Wald test	
LQ	5.8 **	12.0 ***	2.90 *
LPE	5.7 **	8.2 ***	6.33 ***
LY	19.0 ***	128.0 ***	7.65 ***
LAC	2.8 *	5.2 **	12.82 ***

Notes: The reported statistics are distributed as chi-square with degrees of freedom equal to the number of cointegrating relationships. ***, ** and * indicate rejection of the null hypothesis at the 1%, 5% and 10% significance level, respectively.

The implied cointegrating relationship is obtained from the standardized β' eigenvector displayed in Table 4. This relationship can be interpreted as the long-run residential electricity demand which can be rewritten as follows (t values in parentheses):

$$(10) \quad \ln Q_t = \underset{(3.77)}{0.791} - \underset{(-2.13)}{0.210} \ln PE_t + \underset{(7.26)}{1.312} \ln Y_t + \underset{(4.18)}{0.223} \ln AC_t$$

All the variables in the model are statistically significant and are correctly signed. Overall, these estimates suggest that the residential demand for electricity increases with an increase in real incomes and net additions in the stock of air conditioners, while it decreases when the real price of electricity rises. In particular, results indicate that the long-run price elasticity of residential electricity demand is -0.21. This indicates that a 10% increase in the price of electricity provokes a 2.1% decrease in its demand, all else equal. On the contrary, electricity demand appears to be elastic to income in the long-run, as the long-run income elasticity estimate 1.31. This estimate suggests that a 10% increase in average household income cause in the long-run a 13.1% increase in residential electricity demand. More interestingly, results show that durables do matter to forecast residential demand. The estimations show that the elasticity of electricity demand with respect to the stock of air conditioners is 0.22. This indicates that a 10% increase in the stock of air-conditioning equipment ends in a 2.2% increase in residential electricity demand. [18]

The results of the long-run model can be used to examine the individual contribution of prices, income and stock of air-conditioning equipment throughout the 10 year period we examined. They can also be used to predict the possible evolution of residential demand in future years. In the first case, we calibrated the model using average initial and end sample values to compute the individual contribution of each independent variable on residential electricity demand. Results indicate that the increase in the stock of air-conditioners explain, in relative terms, about 44% of the 25% increase in the per-customer electricity demand observed between 1997 and 2006. The decline in real prices caused by the regulatory tariff freeze explains 36% of the increase in demand, while the remaining 20% is due to the improvement in real per-capita incomes. Of course, the increase in the stock of air-conditioners is probably due to the notably reduction in the cost of their use.

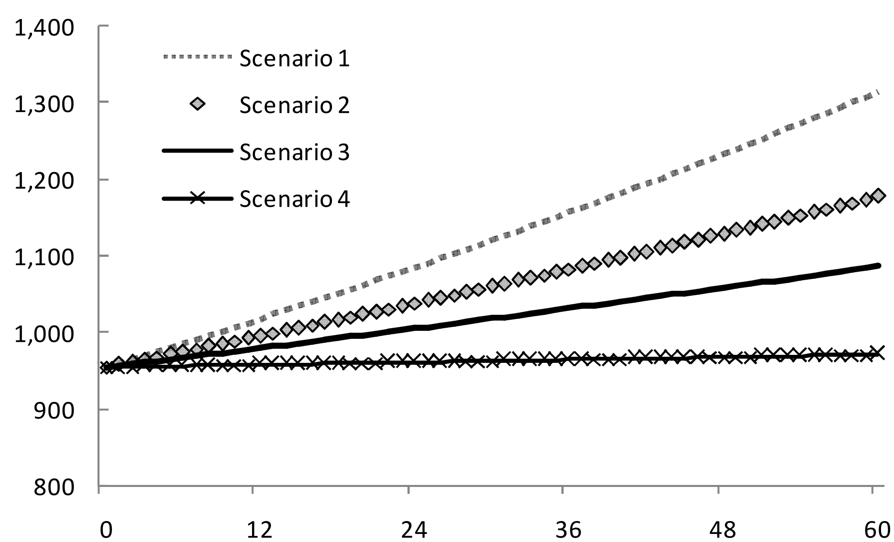
We also used the parameters of the model to evaluate future energy consumption scenarios for the Greater Buenos Aires. We simulate four scenarios whose forecasts all run from 2006 to 2011. The first scenario shows the demand pattern if the price freeze remains unmoved, real incomes improve 1.5% per year and the stock of air-conditioners increases at the same average rate of the last decade, 10.5% per year. Of course, real prices in this case

[18] Results are quite robust to the alternative measures of the stock of air conditioners. For example, when we used the EA(1.50) series, the long-run estimates are -0.22 (price elasticity), 1.43 (income elasticity) and 0.29 (air-conditioners stock elasticity). When we use the EA (1.75) series, long-run elasticities increase to -0.26 (price elasticity), 1.62 (income elasticity) and 0.38 (air-conditioners stock elasticity).

decrease because of the inflation rate, which we estimate at 10% per year. The second scenario supposes that real residential electricity prices remain unchanged, while income and air-conditioners increase at the same rates of the first scenario. The third scenario supposes that the price freeze is stopped and that, by 2011, real prices converge gradually to pre-intervention levels. In this case we also assume that real incomes would grow at 1.5%, and that the stock or air-conditioners increases at the same path of scenarios one and two. The fourth scenario mimics the third, though it supposes that the stock of durables remains unchanged (i.e., this scenario supposes that durables are ignored when predicting future demand).

Figure 2 displays the evolution of total residential demand for the four scenarios defined above.[19] The figure shows that the possible evolution of the variables can have a significant impact on residential demand, as the gap between the extreme forecasts is 343 GWh, or 36% of initial demand. For instance, results for scenario 1 suggest that if the price freeze remains unchanged, by 2011 total residential demand in Buenos Aires would total to 1,314 GWh per month, but if the price freeze is lifted and real prices remain unchanged – the hypothesis of scenario 2 – , monthly demand would come to 1,177 GWh. In other words, the difference between lifting the price freeze and keeping 2006 real tariffs unchanged would equal, in five years time, to about 15% of 2006 total residential demand.

Figure 2
Predicted Total Residential Electricity Demand
Greater Buenos Aires; In GWh, 2007-2011



[19] Projections of total residential demand result from multiplying the forecasted demand per-residential user by the total number of users, which in 2006 was 4 million. To avoid the superposition of effects, the projections assume that the number of total users remains unchanged.

Scenarios 3 and 4 both suppose that the price freeze is stopped and that, by 2011, real prices converge to pre-intervention levels. The difference between the two is the inclusion in the forecast of the growth rate of the stock of air-conditioners. Results indicate that if air-conditioners are considered in the projection, total residential demand by 2011 is forecasted at 1,086 GWh, while if the growth of those durables is ignored, total residential demand in Buenos Aires would come to 971 GWh. To put this result into perspective, the 10% difference between the two forecasts (for Buenos Aires only) represents 12% of total residential demand in 2006, or about 0.7% of total installed generation capacity in the country.

c. Estimation of the short-run error correction model

The vector of estimates obtained using the Johansen approach represents the long-run relationship among the variables. To model the demand for electricity more generally, the next step involves estimation of the short-run VAR in error correction form (VECM) with the cointegration relationships explicitly included. This VECM can be written as follows:

(11) $$\Delta z_t = \Gamma_1 \Delta z_{t-1} + \ldots + \Gamma_{k-1} \Delta z_{t-k+1} + \gamma \hat{\beta}' z_{t-k} + \Psi D_t + \varepsilon_t$$

where $\beta' z_{t-k}$ is the error correction term (ECT) obtained from the long-run relationship and represents deviations in electricity consumption from its long-run mean. The coefficient γ measures the speed of adjustment in current consumption to the previous equilibrium demand value. An initial version of the model with 12 lags was estimated and lag exclusion tests for each lag were used to examine possible reductions in the number of lags. For each lag the χ^2 (Wald) statistics for the joint significance of all endogenous variables at that lag were estimated for each equation separately and jointly. Results suggest that the null hypothesis of significant lag cannot be rejected up to the eighth lag. The VECM was thus estimated over the period 1997-2006 with 8 lags.

Table 6 reports the results of the short run residential demand of electricity. Each column presents the coefficients for the current period (t) up to lags of 8 months (t-8), while the last column reports the sum of the lagged coefficients. The model fit is relatively high as the coefficient of variation is 0.89. There are no signs of residual autocorrelation or autoregressive conditional heteroskedasticity. The Lagrange multiplier test through 8 lags is 13.78, which is below the χ^2 critical value with 16 degrees of freedom of 26.29 at the 5% level. The White heteroskedasticty test is lower than the χ^2 critical value with 710 degrees of freedom at the 5% level of 773.1.

Table 6
Short-run residential electricity demand

	t	t-1	t-2	t-3	t-4	t-5	t-6	t-7	t-8	Total effect
D.LQ		1.22***	-1.56***	1.52***	-1.74***	1.34***	-1.10***	0.55***	-0.41***	-0.192
		(10.51)	(-9.25)	(6.79)	(-7.15)	(5.56)	(-5.02)	(3.43)	(-4.24)	
D.LPE		0.04	0.04	0.02	-0.13***	-0.08	-0.06	0.01	-0.05	-0.212
		(0.70)	(0.58)	(0.40)	(-2.36)	(-1.19)	(-1.05)	(0.11)	(-0.94)	
D.LY		-0.10	-0.13	-0.08	-0.06	-0.01	-0.06	-0.01	-0.01	-0.467
		(-0.99)	(-1.25)	(-0.85)	(-0.72)	(-0.16)	(-0.80)	(-0.09)	(-0.16)	
D.LAC		-0.53***	0.12	-0.07	-0.38*	-0.25	0.41*	0.04	-0.73***	-1.406
		(-2.65)	(0.53)	(-0.34)	(-1.75)	(-1.07)	(1.76)	(0.17)	(-3.20)	
ECT		-0.15								
		(-2.53)								
LCDD	0.000									
	(-0.883)									
LHDD	0.000									
	(0.638)									
D2002	-0.01*									
	(-1.789)									
Constant	0.01***									
	(2.798)									
Adjusted R^2		0.891								
F statistic		24.39								
LM(9)		13.64								
Heteroskedasticity		742.14								

Notes: A D preceding the variables means that they are the first differences of natural logs. t ratios in parenthesis. ***, ** and * indicate rejection of the null hypothesis at the 1%, 5% and 10% significance level, respectively.

Overall, the coefficient estimates are of reasonable magnitude and correctly signed according to theory. The short-run elasticities are smaller than the long-run elasticities implied by the model in levels (the long-run model). Results of the first row indicate that growth in electricity consumption in the previous eight months has a persistent and significant effect on current consumption. The sum of the impact, which is reported in the last column of Table 6, is -0.19. All individual coefficients are statistically significant. This negative impact reduces the effect of any permanent change of the growth rates in the independent variables.

The coefficients of the second row indicate that the impact of changes in the real price of electricity on current consumption is -0.212 (from the last column of Table 5). However, the only significant individual effect corresponds to lag of 4 months which has a coefficient of -0.133. This coefficient suggests that a change in the real price of electricity four periods before has a significant impact on current consumption. But as a result of the effect of lagged electricity consumption, the total impact of a 10% increase in the real price of electricity is to reduce current consumption by 1.11%.[20] This figure is smaller than the long-run price elasticity of -0.21%.

Results also indicate that the impact of changes in real income on current electricity demand is -0.467. However, all coefficients are not significant statistically. This suggests that an increase in real income has no significant effect on electricity demand in the short run. This is reasonable given the monthly frequency of the data. But in the long run a 10% increase in real income leads to a 13.1% increase in electricity consumption. Contemporaneous increases in the stock of air-conditioners reduce consumption growth by -1.406. The significant effects are at lags of 1, 4, 6 and 8 months, which gives a total impact of -1.24. This is an unexpected result as the long-run elasticity of electricity demand to the stock of air conditioners is positive, 0.22. Finally, the error correction term (ECT) is statistically significant and has a coefficient of -0.15, which indicates that when demand is above or below its equilibrium level, consumption adjusts by 15% within the first month.

6. Comparison with recent studies

Several recent studies have examined the determinants of residential electricity demand. Table 7 summarizes the price and income elasticity estimates of studies that are sufficiently similar in objective and technique to justify comparison. The table highlights the substantial variation in short- and long-run estimates of both the price and income elasticities of demand for residential electricity. The short-run price elasticity estimates range from -0.14 to -0.63, while long-run estimates vary from -0.16 to -0.54. For the short-run income elasticity, the range is 0.01 to 0.66, while long-run estimates vary from 0.32 to 1.56. Presumably, some of this variation stems from differences in types of data and the treatment of prices and other variables that enter the estimated models.

Our estimates for the short- and long-run price elasticities of -0.13 and -0.21, respectively, are at the bottom of the range of previous estimates. These results are somehow expected, since the price freeze that dominated the second-half of our series made real prices to decline considerably, about 45%. Therefore, the elasticity estimates show the aggregate response to demand to a price decline, which is smaller than the impact of demand to a price increase. To put this result into perspective, we looked at the evolution of real prices in other studies, but we found only two. Bentzen and Engsted (1993) compute a long-run price elasticity estimate of 0.45 using a price series that show a real increase of 77%, while Holtedahl and Joutz's (2004) estimate of 0.16 comes from a sample period in which real

[20] This figure is obtained by dividing the impact of price changes on electricity demand (-0.133) by one minus the total impact of past growth in electricity demand on current demand (-0.19).

prices declined 48%. The real price decline and elasticity estimates of this latter study are similar to ours, which confirms the importance of distinguishing estimates between a own-price increase and a own-price decline.

Table 7
Results for Other Studies using Time Series Data

	Country	Data[1]	Price elasticity SR[2]	Price elasticity LR	Income elasticity SS	Income elasticity LR
Beenstock et al (1999)	Israel	Q; 1973-1994	n.a.	n.a.	0.58	1.09
Bentzen and Engsted (1993)	Denmark	A; 1948-1990	0.13	0.46	0.67	1.21
Dergiades et al. (2006)	USA	A; 1965-2006	0.39	1.06	0.10	0.27
Halicioglu (2007)	Tukey	A; 1968-2005	0.33	0.52	0.44	0.70
Holtedahl y Joutz (2004)	Taiwan	A; 1955-1995	0.15	0.16	0.22	1.04
Hondroyiannis (2004)	Greece	M; 1986-1999	n.a.	0.41	0.20	1.56
Narayan and Smith (2005)	Australia	A; 1966-2000	0.26	0.54	0.01	0.32
Silk and Joutz (1997)	USA	A; 1949-1993	0.63	0.48	0.38	0.52
Zachariadis et al. (2006)	Cyprus	A; 1960-2004	n.a.	0.43	n.a.	1.17

Notes: [1]The A refers to annual data, the Q to quarterly data and the M to monthly data. [2] SR and LR stand for short- and long-run, respectively

The finding that our estimated short-run income elasticity is not statistically significant is not totally unexpected, since it is possible to speculate that residential electricity demand would rarely be impacted by income changes in the short-run. Note that Hondroyiannis (2004), the only previous work to use monthly data, finds a low short-run income elasticity estimate.[21] Table 7 also shows that the income elasticity estimates vary widely across studies. Given the dissimilar definitions of income – from real GDP per capita to real disposable income – and the different periods covered by those works, such variation is somehow predictable. Still, our long-run income elasticity estimate does fall within the fairly broad range of existing estimates. Note that the difference between our estimate and Hondroyiannis' (1.56 – 1.31 ≈ 0.25) is close to our elasticity estimate for air-conditioners. Previous studies without the durables variables may be capturing this combined effect in the income variable (see also Silk and Joutz, 1997).

In fact, our study highlights the relevance of durables. Few time-series studies examine the long-run impact of electric appliances on residential electricity demand.[22] Dergiades and Tsoulfidis (2006) regress total (not per-capita) residential demand on the per-capita occupied stock of housing, used as a proxy for the per-capita stock of electrical appliances,

[21] In this study, the price variable does not enter the Error Correction Model, which seems to indicate that the short-price elasticity also is not statistically significant.
[22] Other studies use an urbanization variable to capture the process of economic development. See for example Holtedahl and Joutz (2004) and Halicioglu (2007).

and find an elasticity estimate of 1.5. In this way, this estimate seems to capture – and combine – the impact of both the evolution of total users, urbanization and the presence of newer house equipped with more durables. It also contrasts with their income elasticity estimate of 0.27, which is the lowest shown in Table 7. Our approach is close to Silk and Joutz's (1997), who construct seasonally adjusted indices of cooling and heating appliances to capture their contribution to demand growth.[23] Their results indicate that the elasticity of cooling appliances is 0.26, which is similar to our 0.22 estimate. This confirms the relevance of durables to examine the long-term pattern of residential electricity demand.

7. Conclusions

The residential demand for electricity and its determinants are of crucial importance for policy. The idea is that the supply of electricity requires the operation of electricity-generating plants that are costly to develop and also take considerable time to become operational. As a result, knowledge of the determinants of the demand for electricity as well as its accurate forecasting are of extreme importance for the examination of an effective energy policy to meet current demand and to anticipate future needs. Furthermore, the energy policy at the local and national level is associated with political debates related to environmental concerns. Having a more precise knowledge of the determinants of demand and their impact can contribute to the making of more informed decisions. For this purposes, it is of critical importance to examine the nature of the electricity demand, that is, whether it is stable or not. A stable demand function indicates that there is a theoretical relationship between the variables involved and so policy proposals can be designed for meeting the current and future demand for electricity.

This paper has examined the determinants of the aggregate residential demand for electricity in the Greater Buenos Aires between 1997 and 2006. During the second half of this period, residential tariffs remained nominally fixed, while an income boom boosted up the sales of durables. For that reason, the econometric specification assumes that the demand for electricity depends on the price of electricity, the per capita income, weather conditions and most importantly the stock of air-conditioning equipment, a variable that has not been examined before in time series studies for developing countries as a determinant of residential demand. We tested the stability of our demand function using cointegration techniques, which showed that there is a single cointegrating relation among the variables involved. Several tests indicate that the econometric specification is appropriate to examine past and future energy policy

[23] In this work, the stock of electricity using appliances related to heating is multiplied by HDD, whereas the stock of electricity using appliances related to cooling is multiplied by CDD.

The results of out study indicate that durables do matter for residential electricity demand. The estimated parameters of our model allow us to compute that the increase in the stock of air-conditioners explain, in relative terms, about 44% of the 25% increase in the per-customer electricity demand observed between 1997 and 2006. The regulatory tariff freeze accounts for 36% of the increase in demand, while the remaining 20% is due to the improvement in real income. The model also highlights the relevance of durables in predicting future demand. For instance, the model predicts that ignoring the growth in the stock of air-conditioners would lead in five years to an underestimate error of about 12% total current residential demand. Furthermore, the model also forecasts that the difference between lifting the price freeze and keeping 2006 real tariffs unchanged would equal, in five years time, to an increase in demand of about 15% of current residential demand.

The findings have important implications. The results indicate that the estimated residential demand for electricity can be used for policy analysis. The parameters of the aggregate residential demand function would make more accurate the forecasting of electricity. Moreover, the results suggest that changes in pricing policy can be an effective instrument for achieving electricity conservation in the long run. In addition, the high-income elasticity in the long run implies that a substantial higher electricity consumption pattern would be expected as households' real incomes converge to that of other countries. Finally, the finding that air-conditioners do have a large impact on demand illuminates the need to examine, at greater detail, the impact of durables on household electricity demand. Policy makers and investors could thus benefit from the findings of this study that provides useful information on the characteristics of the market for residential electricity consumption.

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