Different approaches of modelling reaction lags: How do Chilean manufacturing exports react to movements of the real exchange rate?

by

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Abstract

This study examines the relationship between export supply and the real exchange rate using annual Chilean data for the period 1960-96. The hypotheses to be tested are first, that the real exchange rate does matter for the supply of exports - contrary to studies relying on quarterly data - and second, that the impact of a real depreciation only ceases to be positive and significant after about 2-3 years. Four different distributed lag models were considered as potentially adequate and useful to depict the impact of the real exchange rate over time. Even though all four models assumed different underlying lag structures, they all point to the importance of maintaining a competitive real exchange rate over time. The transfer function model is particularly well-suited in shaping any lag structure in that it is not presumptive in form.

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1. Introduction

Chile, an early reformer in Latin America, undertook many changes in its exchange rate regime and its exchange rate policy in the period between 1960 and 2002[1]. Resulting changes in real exchange rates and their lagged impact on exports are relevant for two reasons: First, the Chilean economy is not only good in exporting but also very dependent on exports. Second, the approach of modelling lags might also be interesting when other countries and/or other economic issues are investigated.

The most important changes in Chilean economic policy occurred in 1973/74 under the military regime of Pinochet (1973-89) when policy-making underwent an orientation towards neoliberal and monetarist thinking. This fully market-oriented economic policy was continued under Aylwin (1990-95) and Frei (1995-2000) to the surprise of many neoliberal economists and political observers who had expected a return to interventionist policy-making under the Christian Democrats. Since then, this policy has even been taken up in general terms by President Lagos who belongs to the socialist party.

It is worthwhile to mention that the exchange rate continued to play an important part in Chilean economic policy making both under Pinochet and the Christian Democrats, Aylwin and Frei. After having removed the multiple exchange rate system of the interventionist days and after having unsuccessfully applied an orthodox anti-inflation policy during 1973 to 1977, the monetarist economic team started to use the exchange rate to tame inflation by pursuing an active crawling peg in 1978/79, causing the rate of devaluation to fall behind the rate of inflation.

The result of real appreciation of the Chilean peso was reinforced and the rate of inflation finally curbed, by fixing the Chilean peso to the US-$ in 1979. This policy found its justification in theories of ‘Global Monetarism’ that considered and suggested fixing the exchange rate as a way to bring down the rate of price increases of an inflation-prone country to the lower world rate of inflation via a shrinking of the supply of money. However, in 1982 the nominal anchor system had to be given up due to unsustainable current account deficits. The currency had to be devalued and in 1984 a more flexible crawling peg regime vis-à-vis the US-$ with an exchange rate band of +/- 5% was introduced. Since 1991 the Chilean peso was fixed to a currency basket consisting of the US-$, the German mark and the yen. The exchange rate band was then extended to +/- 10%. Due to high capital inflows, however, the Chilean peso had to be revalued in nominal terms whenever the lower exchange rate band was reached. Furthermore, real appreciations resulted because the Chilean rate of inflation, though low for Latin American standards, continued to exceed the respective rates of the U.S.A, Germany and Japan. This being the case, Chilean exporters complained louder in the last few years. Given this constant appreciation pressure on the real exchange rate, a flexible exchange rate regime was introduced on September 2, 1999. In 2001, all remaining controls on capital transactions were eliminated (IMF, 2000 and 2002).

The question now is whether an appreciated real exchange rate does harm to exports, and if so, to what extent. Another question is whether the influence of the exchange rate on exports is longer-lasting, and if so, what time period of impacting is to be found in the Chilean manufacturing sector.

De Gregorio (1984a, 1984b) estimated the price elasticity (real exchange rate elasticity) of Chilean industrial exports with annual data in a partial adjustment model (geometric lag/Koyck lag model) from 1960 to 1981. He found their price elasticity to be significant and to take on values of 0.38 in the short run and 1.77 in the long run. These results clearly point to the harmfulness of real appreciations. However, the above mentioned results contrast with an empirical study that was done on Argentine industrial exports by Wohlmann (1998). The period from 1991 to 1995 was analysed with quarterly data. Wohlmann found the price elasticity of industrial exports to be not significant, calling into question the harmfulness of real exchange rate appreciations.

To shed more light onto the debate about the impact of real exchange rate appreciations, this study will seek to develop an adequate macroeconometric export supply model (Chap.2: Static modelling). This model will be extended to describe the reaction pattern of the manufacturing export industry vis-à-vis changes in the macroeconomic environment, with special regard to the real exchange rate (Chap.3: Dynamic macroeconometric modelling by means of distributed lag models). A central assumption of dynamic modelling (geometric lag model, Gamma lag model, polynomial lag model, transfer function model) is that, in general, the response of manufacturing exports takes time to evolve and events having occurred one or more years prior might still have a considerable impact (indeed perhaps their only impact) on the export behaviour of the present. The overall delay in the response of manufacturing exports is assumed to be due to recognition lags, decision lags and production lags so that the overall lag is better measured in terms of years rather than quarters. Major problems and issues concerning the modelling of lags will be addressed in Chap. 3.1. A choice of four macroeconometric distributed lag models will be presented in Chap. 3.2. All these models are dynamic in character by allowing for lagged relationships between the dependent variable (manufacturing exports) and the independent variables deduced from macroeconomic dependent economy models. In Chap. 3.3 various regressions will be run applying these models, the results of which will lead to conclusions for economic policy making and econometric modelling (Chap. 4, sections 4.1 and 4.2).

2. Static modelling

An altered Australian model is used as a framework for modelling the behaviour of exports in the short and long term in response to changes in macroeconomic conditions (macroeconomic data).[2] The Australian model assumes competititive factor and goods markets and is applied to the modelling of small, open economies. It further assumes that export demand is given and can be considered as an exogenous variable. According to the Australian model export supply is determined by relative prices and export demand is determined by both relative prices and real foreign expenditures (Dornbusch, 1980). In the altered Australian model some modifications are made. Export supply (X^s) is assumed to be determined by relative prices (RER), the production capacity (DY) and the domestic income-absorption gap (CAY), i.e. $X^s = X^s(RER, DY, CAY)$. Export demand (X^d) is assumed to be dependent not only on relative prices (RER) but also on real foreign income (FY), i.e. $X^d = X^d(RER, FY)$.

The macroeconomic, independent variables RER, DY, CAY are assumed to have a non-separable impact[3] on the dependent variable XS, namely total manufacturing exports respect. supply thereof, which is the variable we are concerned with (eq. (1):

(1) $$XS_t = a * RER_t^b * DY_t^c * \exp(d*CAY_t) * \exp(u_t)$$

Both dependent and independent variables (please see **Appendix 1: Description of variables**) are measured in real terms with 1986 as base year.

t = time, t = 1960, 1961,....., 1996

XS = manufacturing exports in millions of US-$ (in real terms)

RER = real (export trade weighted) exchange rate

DY = trend of gross domestic (i.e. Chilean) product; was generated by applying the Hodrick-Prescott Filter to real domestic product ; serves as an indicator for production capacity (Khan and Knight, 1988).

CAY = (X-M)/Y = exports (X) minus imports (M) divided by income (Y) =(Y-E)/Y = domestic income (Y) minus absorption (E) divided by income; indicates the ‘income-absorption’-gap or simply domestic demand pressure (Dornbusch, 1980); accordingly export activity is seen as ‘residual’ activity (income-absorption surplus or deficit as a percentage of domestic income); the introduction of the 'easy to calculate' CAY-variable goes back to Sjaastad (1981); Faini (1994) and Newman et al. (1995) also emphasize the importance of adding an ‘absorption’ variable to export supply models; the ‘absorption’ variable could be e.g. a capacity utilization index which has the advantage of being more precise than CAY if calculated for the manufacturing sector;

u = disturbance/error term with the usual properties. It is normally distributed with the following properties: a) the mean of the disturbance term is zero ($E(u_t)=0$), b) the variance of the disturbance term is constant ($Var(u_t)= s^2_u$), c) the disturbance terms of the periods t and s are uncorrelated ($Cov(u_t, u_s)= 0$), d) the disturbance term is independent of the regressors so that the covariance between the disturbance term and the independent variables is zero ($Cov(rer_t,u_t)=0$, $Cov(dy_t,u_t)=0$, $Cov(cay_t,u_t)=0$).

Equation (1) can be made estimable by putting (1) into its log-linear form (2). Doing this has the well-known advantage that the regression coefficients can be interpreted as elasticities (except for the coefficients a and d [4]) .

(2) $xs_t = a + b*rer_t + c*dy_t + d*cay_t + u_t$

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with:

xs = LOG(XS), rer = LOG(RER), dy = LOG(DY), cay =CAY

u = disturbance/error term with the usual properties

and +/- signs as the hypothesized signs of the regression coefficients:

a: there will always be positive autonomous exports

b: a devaluation of the real exchange rate (increase or rer) will lead to an increase in export supply by making the export of manufacturing exports more profitable; at the current world market price this supply will be totally absorbed by export demand c: a rise in trend of domestic product (dy) is assumed to go hand in hand with a proportional increase of production capacity which will translate into an increase in export supply

d: whenever real expenditures decrease and (ceteris paribus) cay increases (e.g. because of expenditure-reducing policies), export supply is assumed to increase (Faini, 1994).

3. Dynamic macroeconometric modelling by means of distributed lag models

The basic model, presented in section 2, will now be made dynamic and then applied to stationary (suffix z), annual Chilean data from 1960 to 1996[5].

3.1 Working with lags

The static model of Chap. 2 can be formulated as a distributed lag model of the following form:

$$(3)\quad xsz_t = a + \sum_{i=0}^{\infty} b_i * rerz_{t-i} + \sum_{i=0}^{\infty} c_i * dyz_{t-i} + \sum_{i=0}^{\infty} d_i * cayz_{t-i} + u_t$$

It is assumed with this type of model that a one-time change in rerz (dyz, cayz) will affect the expected value of xsz in every period thereafter. When the duration of the lagged effects is considered extremely long (∞ periods), infinite lag models (such as the well-known geometric lag model or the rather unknown Gamma lag model) which have effects that gradually diminish over time can be used. When changes in rerz (dyz,cayz) cease to have any influence after a fairly small number of periods (k periods), finite lag models (such as the the well-known polynomial lag model or the rather unknown transfer function model) can be applied.

The coefficients b_0, c_0, and d_0 are the impact multipliers/short-run multipliers. The long-run multiplier is the total effect, for instance b = $\sum_{i=0}^{k} b_i$ (for c, d respectively).

Whereas the operation with lags is theoretically easily formulated (see equation (3)), in practice it is extremely difficult to determine the maximum lag length and the structure of the lags, i. e. the distribution of the lag coefficients (Wohlmann, 1998).

Junz and Rhomberg (1973) found that it could take 3-5 years (with a peak for the four-year lag) for the full lagged effects of changes in the exchange rates to manifest themselves (Cotsomitis et al., 1991). Therefore in the econometric part (see Chap. 3.3), an average 4 year-lag, was used as the maximum lag length with respect to changes in the real exchange rate, in order to save degrees of freedom. For several reasons no lags were plugged in for dyz and cayz - with the exception of the transfer function model -: *First*, the use of annual data facilitates our work since seasonal fluctuations do not have to be considered, i.e. seasonal lags do not have to be built in. *Second*, the series dyz shows a very steady and stable development. Therefore, it does not matter from the econometric/statistical point of view whether current or lagged values are used. *Third*, cayz is definitely an indicator of the present. It runs parallel with the development of exports. *Fourth, and most important*, the main interest of this article is to describe the reaction pattern of manufacturing exports vis-à-vis the real exchange rate, the importance of which for economic policy must be scrutinized by econometric means.

3.1.1 Determining the lag length

In order to determine the lag length, Greene (2000) suggests to look at models with different lag lengths and then compare the adjusted R^2 and Akaike's information criterion (AIC) of these models. Besides, sequential F tests can be performed on these models.

However, to determine the correct lag length, one should not only rely on the statistical criteria just mentioned, but also look at the data, i.e. the cross correlation functions, rule of thumb-values, and the values estimated in other econometric studies.

3.1.2 Determining the lag structure

Also of importance is the determination of the lag structure or, that is, the distribution of the lag coefficients. Under the assumption that the model has been specified correctly and contains all the relevant variables, one should take a look at the cross correlograms (cross correlation functions of the stationary series which are characterized by the suffix z ; see also beginning of section 3.3) between the dependent variable xsz and the independent variables rerz, dyz, cayz.

The following chapter presents the geometric lag model and the Gamma lag model. We will also utilize the polynomial lag model and search for the degree of the polynomial which best reproduces the lag structure revealed by the cross correlations. Finally, the transfer function model will be presented, which is superior from a theoretical point of view in that it can model any lag structure[6].

3.2 Distributed lag models and eligible estimation methods

3.2.1 The geometric lag model

The geometric or Koyck lag model allows for infinite lags thereby avoiding the problem of how to determine the appropriate lag length. It assumes a geometrically declining lag structure. Arbitrarily small weights are assigned to the distant past (see (4') and (4'') and figure 1, appendix 2).

(4) $xsz_t = a + \sum_{i=0}^{\infty} b_i \,*rerz_{t-i} + c*dyz_t + d*cayz_t + u_t$

(4') $xsz_t = a + (b_0(1-l)\,l^{0})*rerz_t + ... + (b_0(1-l)\,l^{\infty})*rerz_{t-\infty} + c*dyz_t + d*cayz_t + u_t$

(4'') $xsz_t = a + (b_0(1-l))\sum_{i=0}^{\infty} l^{i}*rerz_{t-i} + c*dyz_t + d*cayz_t + u_t$

with $b_i = b_0(1-l)\,l^{i}$, $i = 0,1,2,...,k$ and $0 \leq l \leq 1$

The equations (4') and (4'') have been formulated in moving average form. As it is well known, they can be transformed into (5), the autoregressive form of the geometric lag model[7], which is best suited to estimation of the partial adjustment model.

(5) $xsz_t = a' + b'*rerz_t + c'*dyz_t + d'*cayz_t + l*xsz_{t-1} + v_t$

with $a'=a(1-l)$; $b'=b_0=b(1-l)$; $c'=c(1-l)$; $d'=d(1-l)$ and

$v_t = (u_t - l\,u_{t-1})$

The following formulas allow us to calculate (Greene, 2000):

(i) The mean lag $q_{av.} = l / (1 - l)$

(ii) The median lag $q^* = \ln 0.5 / \ln l$

(iii) The impact multiplier is $b_0 = b_0^* l^0$

(iv) The long run multiplier is $b_k = b_0 \sum_{i=0}^{k} l^i$;

However, only under the assumption that the disturbance terms are not autocorrelated, will OLS result in an asymptotically efficient estimator for the partial adjustment model. Therefore, before applying OLS, a LM test on autocorrelation must be performed and any problem corrected[8] by the FGLS (Feasible General Least Squares)-technique (Greene, 2000). Although this is a quite cumbersome procedure, FGLS does generate efficient and consistent, though biased estimators (Kelejian and Oates, 1981).

3.2.2 The Gamma lag model

The Gamma lag model is similar to the geometric lag model in that it assumes infinite lags, thus circumventing the problem of determining the lag length. The Gamma lag model assumes first a very short increase and then a steadily declining decrease in the lag structure. That is, if after an initial period (of 1 to 2 years) a declining influence of the real exchange rate on manufacturing exports is hypothesized, the Gamma lag model becomes relevant. It takes the following form:

(6) $xsz_t = a + b\sum_{i=0}^{\infty}(i+1)^g\ l^i * rerz_{t-i} + c* dyz_t + d* cayz_t + u_t$

This equation can be transformed into

(7) $xsz_t = a + b* grerz_t + h_t + c* dyz_t + d* cayz_t + u_t$

with $0 \leq l \prec 1$; $0 \prec g \prec 1$; $grerz_t$[9] $= \sum_{i=0}^{t-1}(i+1)^g\ l^i * rerz_{t-i}$

and $h_t = b\sum_{i=t}^{\infty}(i+1)\ (i+1)^g\ l^{i\,*} rerz_{t-i} \rightarrow 0$[10]

If g and l are allowed to take on any value between 0 and 1, the maximum likelihood estimation of g, l,a, b, c, and d will minimize the sum of squared errors. Given g and l (hence given grerz), the estimation of b is linear. The procedure is therefore to „search“ over g and l, picking those values that minimize the above sum of squares. The ML (Maximum Likelihood) - method generates estimators with the desired properties, namely unbiased and efficient estimators. Alternatively a non-linear least square procedure that relies on an iterative process might be used (Schmidt, 1974).[11]

The gamma lag can be described by figure 2 (appendix 3):

3.2.3 The polynomial lag model

The polynomial lag model (Almon lag model) is a finite lag model. It has two advantages when compared to the models of 3.2.1(geometric lag model) and 3.2.2 (Gamma lag model): *First*, in contrast to the geometric lag and the Gamma lag models which require sophisticated estimation techniques such as FGLS or ML or non-linear estimation procedures, the polynomial lag model relies on the OLS-technique. *Second*, the polynomial lag technique allows one to model any lag structure that can be expressed by a polynomial of degrees 1,...., p (some finite number).

The major disadvantage of the Almon lag technique is the difficulty of determining the length and the structure of the lag. The consequences of error in specifying the lag length and the order of the polynomial are severe. The problem of misspecifying the lag length and the lag structure is of course aggravated when monthly or quarterly data are used, because extremely accurate information on reaction lags would be necessary in order not to miss the true lag length and the true degree of the polynomial when dealing with monthly or quarterly time-series (Wohlmann, 1998).

Suppose that economic theory and/or the cross correlations suggest that a second-degree polynomial is appropriate to describe the form of the lag (see figure 3, appendix 4).

As it is well known, we would take $b_i = a_0 + a_1 i + a_2 i^2$ (i denoting lag i) and the polynomial lag model would be of the following form:

(8) $xsz_t = a + a_0 (\sum_{i=0}^{k} rerz_{t-i}) + a_1 (\sum_{i=0}^{k} i * rerz_{t-i}) + a_2 (\sum_{i=0}^{k} i^2 * rerz_{t-i}) + c*dyz_t + d*cayz_t + u_t$

Then the OLS estimators of the b's (the coefficients of the lagged rerz) could be calculated according to the following formulas (Kelejian and Oates, 1981):

$b_0 = a_0$

$b_1 = a_0 + a_1 + a_2$

$b_2 = a_0 + 2a_1 + 4a_2$

3.2.4 The transfer function model (autoregressive distributed lag model)[12]

Like the polynomial lag model, the transfer function model (autoregressive distributed lag model) has the advantage of allowing a great deal of flexibility in the shape of the lag distribution. However, unlike the polynomial lag model it does not truncate the distribution at an arbitrarily chosen point and nor does it require an estimate of the degree of the polynomial (Greene, 2000). Thus misspecification of lag length and lag distribution can be avoided, making the transfer function model the model of choice.[13]

The transfer function model takes the following form:

(9) $xsz_t = m + A(L)rerz_i + c*dyz_t + d*cayz_t + u_t$

with $A(L) = B(L)/C(L)$ and $a_0, a_1, a_2 ...$ = the coefficients on 1, L, L^2 ,..in B(L)/C(L) and b_i resp. g_i ....= the coefficients on L^i in B(L) resp. C(L).

B(L) and C(L) are polynomials in the lag operator. The ratio of the two polynomials in the lag operator A(L) can produce essentially any desired shape of the lag distribution with relatively few parameters.[14] For example, if both B(L) and C(L) are quadratic then we get:

(10) $xsz_t = m(1-g_1-g_2) + g_1*xsz_{t-1} + g_2*xsz_{t-2} + b_0*rerz_t + b_1*rerz_{t-1} + b_2*rerz_{t-2} + c*dyz_t - cg_1*dyz_{t-1} - cg_2*dyz_{t-2} + d*cayz_t - dg_1*cayz_{t-1} - dg_2*cayz_{t-2} + (u_t - g_1u_{t-1} - g_2u_{t-2})$

Equation (10) is referred to as an autoregressive distributed lag model with a moving average (MA) disturbance. It should be noted that OLS estimation, a linear estimation technique, will lead to consistent estimates, but that it can only be applied when there are no moving average terms.[15]

When there are moving average disturbances, the model becomes non-linear. In this case, the non-linear least square estimator will be consistent and asymptotically normally distributed (Greene, 2000).

For obtaining a_0, a_1 and a_2 we start from the following relationship: A(L)*C(L) = B(L).

We get the following formulas:

no lag: $a_0 = b_0$ = b_0

1-period lag: $a_1 = b_1 + a_0 g_1$ = b_1

2-period lag: $a_2 = b_2 + a_0 g_2 + a_1 g_1$ = b_2

3.3 Presentation and discussion of the results

The data requirements were two-fold : *First*, all variables had to enter the regression equation in real terms[16] (see Appendix 1 for a description of the variables) . *Second*, all variables / time-series had to be transformed into stationary series in order to avoid the problem of running spurious regressions (Granger and Newbold, 1974, Phillips, 1986 and Darnell 1994). Stationary series will be characterized by the letter z, generating xsz, rerz, dyz and cayz.

Stationarity of the time series was tested by the Augmented Dickey-Fuller test. The original time series in levels (XS, RER, DY, CAY) were found to be non-stationary, but co-integrated (Johansen, 1988 and Darnell 1994). Therefore, a long-run equilibrium between the variables without delays in any explanatory variable could be assumed.

However, our interest lies in the short-run/medium-run relationship between the export supply and its macro determinants as well as in the quantification of the lagged effects. When analysing the short-run/medium run, one wants to control for time trends in the variables which cause non-stationarity of the series and spurious regressions. Therefore, the series have to be made stationary. In the econometric literature two methods are recommended for obtaining stationarity: 1) regressing the time series as a simple linear (or higher order) function of time and then using the residuals as the detrended series or 2) utilizing first (or higher) differences of the time series. However, both methods have severe shortcomings. Method 1 fails when the time series are generated by a random walk with drift since the residual would not be stationary. Time series characterized by growth (such as XS and DY) are quite certainly characterized by a random walk with drift. The problem concerning method 2 is that it assumes a 100% autocorrelation between the disturbance terms at any point of time, which will rarely be the case. Therefore, the author used a third method in order to obtain stationary series. By this third method the variables are freed from short-run disturbances (autocorrelation). On the other hand, however, they retain the ability to 'carry' all relevant information.

By applying a simple model without distributed lags (equation (2)), the general functioning of method 3, which proceeds basically as FGLS (feasible generalized least squares) shall be demonstrated:

(2) $xs_t = a + b * rer_t + c * dy_t + d * cay_t + u_t$

First, a, b, c and d are to be estimated by OLS, provided that the regressors can be considered as exogenous. Second, the estimated values for a, b, c, and d are plugged into eq. (2) and then the estimated values ($evxs_t$) of xs_t are calculated. Third, the estimated values (evu_t) of u_t are calculated according to $evu_t = xs_t - evxs_t$. Forth, a simple regression (eq. (2')), based on a verified first order autocorrelation, is run:

(2') $evu_t = r * evu_{t-1} + e_t$

and r is estimated. Fifth, stationary series (xsz, rerz, dyz and cayz) are produced by removing the autocorrelation part from each variable:

$xsz_t = xs_t - r * xs_{t-1}$; $rerz_t$, dyz_t and $cayz_t$ are generated analogically.

The exogenity/endogenity of the variables rerz, dyz and cayz (stationary variables in LOG-form) was tested in each of the distributed lag models with the Hausman test.[17] The test results were negative. This is to say that the regressors rerz, dyz and cayz were considered sufficiently exogenous to be estimated by non-TSLS-methods.

In subsequent steps the distributed lag models were subjected to two further tests:

The Chow Breakpoint tests were applied, assuming structural change in the year 1974[18]. No structural change could be detected for $a = 0.05$ and $a = 0.01$ in any of the models.

The Breusch-Godfrey Serial Correlation LM tests to diagnose autocorrelation were conducted. These tests were all negative for $a = 0.01$ and 0.05 indicating that autocorrelation did not constitute a problem.[19]

3.3.1 Results of the geometric lag/partial adjustment model

The following regression results (see **table 1**) were obtained - on basis of equation (5) -:

$$\mathbf{xsz_t = 0.70 + 0.43\ rerz_t + 0.10\ rerz_{t-1} + 0.04\ rerz_{t-2} + 0.02\ rerz_{t-3} + 0.98\ dyz_t + 0.94\ cayz_t + 0.41\ xsz_{t-1}}$$

rerz, the variable we are most interested in, displayed a short-run elasticity of 0.43 and a long-run elasticity of 0.73.

Table 1:
Regression results of the geometric lag/partial adjustment model (see equation (5))

Variable	coefficient	short-run elasticity/ value	long-run elasticity[1]/ value	t-statistic	p-value significance(**)
constant	a’	0.70	1.19	2.01	0.05**
rerz $rerz_{t-1}$ $rerz_{t-2}$ $rerz_{t-3}$	$b'=b_0$ b_1 b_2 b_3	0.43 0.10 0.04 0.02	0.73	3.94 3.33 2.00 2.00	0.00** 0.00**[2] 0.05** 0.05**
dyz	c’	0.98	1.66	2.06	0.05**
cayz	d’	0.94	1.59	1.23	0.23
$x5z_{t-1}$	l	0.41	0.69	3.04	0.01**
R-squared R^2 adjusted		0.75 0.71	Chow-Breakpoint-Test (H_o: no structural change)		no rejection of H_o (Prob.:0.65)
Hausman-Test (H_o: exogenity of cayz/dyz/rerz; prob.: 0.89 each)		no indication of endo-genity	Breusch-Godfrey-Serial Correlation LM-Test (H_o: no serial correlation)		no rejection of H_o (Prob.. 0.74)
S.E. of regression		0.16	Log likelihood		17.05
sum squared resid.		0.77	Prob(F-statistic)		0.00**

** : significant for a = 1% (5%); * : significant for a = 10%

[1] Long-run coefficient = short-run coefficient/(1- l).

[2] From an intuitive point of view, b_1, b_2, b_3 ($b_i = b_0 (1- l)\ l^i$) have to be significantly different from zero for a = 1% since they are a combination of b_0 and l, two parameters which are also significant for a = 1%. In order to calculate their significance, we assumed independence of b_0 and l and computed the standard deviations/t-values with SPLUS.

3.3.2 Results of the Gamma lag model

The Gamma lag model was estimated by non-linear least squares. The starting value for g was 0.50 and for l it was 0.50. For a, b, c, d and l the OLS/TSLS-values were taken as starting values. Convergence of the estimates was achieved after eleven iterations.

The following regression results (see **table 2**) were obtained -using equation (7)-:

$xsz_t = 1.47 + 0.42\ gerz_t + 1.39\ dyz_t + 0.39\ cayz_t$ *respectively*

$\mathbf{xsz_t = 1.47 + 0.42\ rerz_t + 0.30\ rerz_{t-1} + 0.18\ rerz_{t-2} + 0.10\ rerz_{t-3} + 0.06\ rerz_{t-4} + 1.39\ dyz_t + 0.39\ cayz_t}$

Table 2: Regression results of the Gamma lag model (see equations (6) and (7))					
variable	coeffi-cient	short-run elasti-city/-value	long-run elasticity/-value	t-statistic	p-value/ significance
constant	a	1.47		3.03	0.01**
grerz	b	0.42	0.54	3.29	0.00**
	g	0.54		0.31	0.76
	l	0.49		1.02	0.32
$rerz_t$	b_0	0.42		3.29	0.00**
$rerz_{t-1}$	b_1	0.30		3.23	0.00**[3]
$rerz_{t-2}$	b_2	0.18		3.23	0.00**[a]
$rerz_{t-3}$	b_3	0.10		3.23	0.00**[a]
$rerz_{t-4}$	b_4	0.06		3.23	0.00**[a]

[3] It is extremely difficult to determine analytically the distribution of $b_1, \ldots, b_4$ ($b_i = b\ (i+1)^{g}\ l^{i}$) without making strong assumptions. We assumed independence of b, g and l and kept g and l fixed. The b_is were calculated with SPLUS.

dyz	c	1.39		3.23	0.00**
cayz	d	0.39		0.42	0.67
R-squared R^2 adjusted		0.70 0.64	Chow-Breakpoint-Test (H_o: no structural change; no rejection of H_0; prob.:0.32)		
Hausman-Test (H_0: exogenity of cayz/rerz/dyz;Prob.: 0.69/0.39/0.69)		no indication of endogenity.	Breusch-Godfrey-Serial Correlation LM-Test (H_o: no serial correlation; no rejection of H_0; prob.: 0.38)		
S.E. of regression		0.17	Log likelihood 15.45		
sum squared resid.		0.71	**: significant for a = 1% (5%)		

3.3.3 Results of the polynomial lag model

The polynomial lag model could be estimated by OLS because, as previously shown, the right-hand sight variables proved to be sufficiently exogenous. A second degree polynomial was suggested by the cross correlation function between xsz and rerz.

The following regression results (see **table 3**) were obtained by applying equation (8) and by calculating b_0, b_1, b_2, b_3 and b_4:

$$\mathbf{xsz_t = 1.47 + 0.43\ rerz_t + 0.29\ rerz_{t-1} + 0.19\ rerz_{t-2} + 0.10\ rerz_{t-3} + 0.04\ rerz_{t-4} + 1.39\ dyz_t + 0.39\ cayz_t}$$

Table 3: Regression results of the polynomial lag model (see equation (8))

variable	coefficient	coefficient value/ elasticity	t-statistic	p-value/ significance	
constant	a	1.47	3.03	0.01**	
$rerz_t$	b_0	0.43	3.33	0.00**	
$rerz_{t-1}$	b_1	0.29	2.97	0.01**	
$rerz_{t-2}$	b_2	0.19	1.93	0.06*	
$rerz_{t-3}$	b_3	0.10	1.20		
$rerz_{t-4}$	b_4	0.04	0.40		
dyz	c	1.39	3.24	0.00**	
cayz	d	0.39	0.43	0.67	
R-squared R^2 adjusted		0.70 0.64	Chow-Breakpoint-Test (H_o:no structural change)		no rejection of H_0 (prob.:0.30)
Hausman-Test (H_o: exogenity of cayz/ rerz/ dyz; prob: 0.69/0.89/0.69)		no indication of endogenity	Breusch-Godfrey-Serial Correlation LM-Test (H_o:no serial correlation)		no rejection of H_0 (prob.:0.37)
S.E. of regression		0.17	Log likelihood		15.48
Sum squared residuals		0.71	Prob(F-statistic)		0.00**

**: significant for a = 1% (5%)

*: significant for a = 10%

3.3.4 Results of the transfer function model

The results of the transfer function model were derived in two steps. First, our first best eq. (10) had to be estimated. Second, these results were used when computing the coefficients we are interested in (see section 3.2.4; eq. 9). When running the regression (eq. (10)) with the time series analysis program EViews, a programming problem[20] appeared. It is generally not possible to run a non-linear estimation on the transfer function model

(10) $xsz_t = m(1-g_1-g_2) + g_1\, xsz_{t-1} + g_2\, xsz_{t-2} + ...+ u_t - g_1 u_{t-1} - g_2 u_{t-2}$

with the same parameters g_1 and g_2 for the autoregressive (AR) term (xsz_{t-1} and xsz_{t-2}) and the moving average (MA) term (u_{t-1} and u_{t-2}), an important requirement of the transfer function model.

Also, a non-linear estimation of the following ARMAX-model

(11) $xsz_t = a + g_1\, xsz_{t-1} + g_2\, xsz_{t-2} +......+ u_t - d_1 u_{t-1} + d_2 u_{t-2}$

was not feasible due to a near singular matrix. In addition, equation (11) would be clearly different from equation (10) with respect to the MA term. The estimation of d_1 and d_2 would not only be irrelevant to this study but its inclusion would also change the values of the other coefficients with which the study is concerned.

Since the non-linear estimation usually takes the linear estimates (the OLS-estimates) as starting values, it was decided to use the linear estimation as an approximation for the non-linear technique [21] . Indeed, one can argue that linear estimation will only lead to inconsistent estimates whereas non-linear estimation (under EViews) would have led to inappropriate and incorrect estimates by calculating d_1 and d_2.

Therefore the (linear) transfer function model was used.

The lag structure was modelled by means of a transfer function. The transfer function had a second degree polynomial both in the numerator and the denominator. For regression results see table 4.

Table 4:
Regression results of the transfer function model (linear estimation; see equations (9) and (10))

variable	coefficient	elast./value of coefficient	t-statistic	p-value/ significance
results of step 1 (preliminary results based on eq. 10):				
constant	m $m(1-g_1-g_2)$	1.22 1.09	2.64	0.01**
(eq. 10) $rerz_t$ $rerz_{t-1}$ $rerz_{t-2}$	 b_0 b_1 b_2	 0.40 0.04 0.16	 3.25 0.26 1.26	 0.00**
C(L)-var $x5z_{t-1}$ $x5z_{t-2}$	 g_1 g_2	 0.37 -0.26	 2.06 -1.56	 0.05** 0.13
results of step 2 (final results based on eq. 9):				
constant (eq. 9)	m	1.22	2.64	0.01**
(eq. 9) $rerz_t$ $rerz_{t-1}$ $rerz_{t-2}$	 $a_0 = b_0$ $a_1 = b_1$ $a_2 = b_2$	 0.40 0.19 0.13	 3.25 1.28[4] 0.54[a]	 0.00**
dyz_t	c	1.41	2.68	0.01**
$cayz_t$	d	0.83	0.96	
R-squared R^2 adjusted		0.75 0.69	Chow-Breakpoint-Test (H_o: no structural change)	no rejection of H_0; prob.:0.57
Hausman-Test (not possible)			Breusch-Godfrey-Serial Correlation LM-Test(H_o: no serial correlation)	no rejection of H_0; prob.: 0.98
S.E. of regression		0.15	Log likelihood	19.83
Sum squared residuals		0.62		

**: significant for α = 1% (5%)

* : significant for α = 10%

[4] The standard deviations/t-values were computed with SPLUS. We assumed independence of b_0, b_1 and g_1 and b_0, b_2 and g_2 and kept both b_1 and g_1 and b_2 and g_2 fixed.

The following regression equation (compare eq. (10) was estimated in a *first step*:

$xsz_t = 1.22\ (1\text{-}0.37\text{+}0.26) + 0.37\ xsz_{t\text{-}1} - 0.26\ xsz_{t\text{-}2} + 0.40\ rerz_t + 0.04\ rerz_{t\text{-}1} + 0.16\ rerz_{t\text{-}2} + 1.41\ dyz_t + 0.83\ cayz_{t.}$

For simplicity and analogy with the other three models, the coefficients of the lagged dyz and cayz are not listed in table 4.

In a *second step* the parameters A(L), i. e. : b_0, b_1, b_2, of the transfer function model (compare section 3.2.4; eq. (9)) were calculated according to the relations (A(L)=B(L)/C(L)) stated in section 3.2.4. Recall that the transfer function model (eq. (9)) contains the regression coefficients we are interested in. The following regression equation was obtained:

$\mathbf{xsz_t = 1.22 + 0.40\ rerz_t + 0.19\ rerz_{t\text{-}1} + 0.13\ rerz_{t\text{-}2} + 1.41\ dyz_t + 0.83\ cayz_t}$

4. Conclusions

4.1 Conclusions for economic policy making

The regression results (tables 1 to 4) give strong empirical support to the hypothesis that an increase in the real exchange rate does have an important, positive impact on manufacturing exports.[22] Whereas depreciation is conducive to an export expansion, appreciation of the real exchange rate will lead to a clear decrease in exports. The results showing the coefficient of the current real exchange rate ($rerz_t$) to lie in a range between 0.40 (transfer function model) and 0.43 (geometric lag model, polynomial lag model), indicate quite an elastic reaction of manufacturing exports to changes in the real exchange rate. The partial adjustment model showed a significant adjustment lag (production lag) of about 8 months. The long-run elasticity was calculated to be approximately 0.73. The geometric lag, the Gamma lag, the polynomial lag and the transfer function model revealed by and large the reaction pattern of exports vis-à-vis exchange rate changes in the past. The coefficients for $rerz_{t-1}$, $rerz_{t-2}$ (and $rerz_{t-3}$) were highly significant in the geometric lag, Gamma lag and the polynomial lag model. They showed a steadily declining, but visible impact of past changes in the real exchange rate and point to the importance of establishing and maintaining a competitive real exchange rate. A common feature of the models was that production capacity (dyz) was always statistically significant, whereas domestic expenditures/demand conditions (cayz) never was[23]. The real exchange rate (rerz) was positive and highly significant in all distributed lag models for $a = 1\%$.

Since the real exchange rate (of the current period and the two preceding years) must be considered an important determinant for export decisions, the economic policy should be carefully calibrated to counter the negative effects of an appreciated real exchange rate. A 10%-appreciation of the real exchange rate will cause manufacturing exports to decrease between 4.0% and 4.3% - according to the models applied (see tables 1 to 4) -. Even past appreciations of the real exchange rate will have a significant impact on exports. Therefore, a nominal anchor policy (the Argentinian type in the period of 1991-2001)[24] or a currency peg, such as the pegging of the domestic currency to a currency basket with the possibility of fluctuation within a certain range (the Chilean type in the period of 1991-1999)[25] must be closely monitored whenever the domestic rate of inflation exceeds that of the pegging partner(s) and appreciation tendencies appear.

These results of a positive, significant relationship between export supply and real exchange rate are not necessarily in line with studies based on quarterly data. For example, a comparable study by M. Wohlmann (1998) found an insignificant and unsystematic[26] relationship between export supply and real exchange rate. This phenomenon seems to be caused by a tremendous short-run variability of the data under consideration. It is extremely difficult to discover the lag structure of quarterly time series relationships due to seasonal and/or one-time fluctuations in these data. This problem will persist - even tough in a weaker form - if the data have been both seasonally adjusted and prewhitened according to Jenkin's method before entering the regression equation (Jenkins, 1979).

4.2 Econometric conclusions

The explanatory power (adjusted R-squared) of the four models presented above lies in the range of 0.64 and 0.71 (see tables 1 to 4). It is highest for the geometric lag (partial adjustment model) and the transfer function model with 0.71 and 0.69. The Log-likelihood value of the transfer function model was highest. The geometric lag model and the Gamma lag model allow the straightforward calculation of short-run elasticities, long-run elasticities and adjustment lags (i.e. production lags).

In principle, all models are suited to describe the reaction pattern of export supply to changes of the real exchange rate of current and past periods. The results obtained are stable and robust. They give strong statistical support for the hypothesis that the real exchange rate ($rerz_t$) does have a significant, positive impact on export supply, regardless which model is applied. The coefficients (b_1 and b_2) of $rerz_{t-1}$ and $rerz_{t-2}$ were highly significant in the polynomial lag model. Since in this model the b_is are a linear combination of b_0 and other parameters, their standard deviations and corresponding t-values are easy to compute. As far as the other three models are concerned, one has to keep in mind that the b_is are a non-linear function of b_0 and other coefficients, thus making statements concerning their significance difficult. It is extremely complicated to determine analytically their distribution. Under certain assumptions (e. g. independence) SPLUS computed highly significant values for them. However, when the assumption of normal distribution is not fulfilled, the standard deviations cease to be a good indicator of 'spread'. This problem might have been present when calculating the t-value of the b_is in the transfer function model.

Nonetheless, the transfer function model has the most desirable properties by allowing one to shape any lag structure (not only a geometric lag, a Gamma lag and a polynomial lag structure). In this study cross correlations justify, by and large, the use of all four models[27], however in other cases cross correlation functions may clearly rule out models with a presumptive form (such as the models of section 3.2.1, 3.2.2 and 3.2.3). It should also be noted that the transfer function model was the model with one of the best Durbin-Watson statistics[28], if one is willing to accept this statistic as a rough indicator for model specification. The study found that EViews had limitations in dealing with the transfer function model, whereas AUTOBOX, a competing time series analysis program, does not have problems in handling transfer functions. However, one should avoid „over-parametrization“ of the transfer function and help AUTOBOX by setting starting values.[29]

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Appendix 1: Description of variables

The data have been taken from statistics of the Banco Central de Chile and the International Monetary Fund (see bibliography under these headings). The deflator for manufacturing exports (DEX) has been provided by Erik Haindl (Universidad de Chile, Departamento de Economía, Santiago de Chile) for the period 1960 to 1986. Banco Central - deflators (Economic and Financial Report, various issues) have been used for the remaining years.

The real exchange rate (RER)

The real exchange rate is the actual, nominal exchange rate adjusted for the relevant price levels at home and abroad. The foreign price level was approximated by the whole sale price index (WPI) of Chile's main trading partners and the domestic price index was approximated by the consumer price index (CPI). This methodology is also used by Chile's Central Bank (compare Banco Central: Economic and Financial Report of March , 1992, p. 11).

It has to be pointed out that the price indices used do not include export subsidies or other incentives for exporting and therefore the real effective exchange rate could not be calculated. However, the real exchange rate was refined by correcting for the importance of Chile's export trade partners.

Since Chile has export-trade relations with a number of foreign countries of varying importance, the pairwise bilateral nominal exchange rates and the foreign WPI’s have to enter the RER-formula according to their export-trade weights. By relying on 14 export-trading partners that make up 80% of Chile's export-trade, the RER has been calculated the following way:

$$\text{RER} = \prod_{j=1}^{J=14} (e_{CHj} * WPI_j \,/\, CPI_{CH})^{wCHJ}$$

with j=1,......,14 trading partners who make up 80 % of Chile's export trade

e_{CHj} = nominal exchange rate between Chile and trading partner j

WPI_j = whole sale price index of trading partner j

CPI_{CH} = consumer price index of Chile

w_{CHj} = export trade weight (percentage of Chilean manufacturing exports going to trading partner j); export trade weights were recalculated for each year and add up to 1 in each year.

RER is an index value with value 1.00 for the base year 1986.

Trend of Chilean GDP (DY)

DY stands for Chilean trend domestic product (GDP). It is used as an indicator for capital stock data/production capacity. It is derived from Chilean GDP in real terms with 1986 as base year.

Chile's real absorption deficit /surplus[30] in relation to real GDP (CAY)

CAY is treated as an indicator for real domestic absorption. It is measured as the percentage share of a current account deficit/surplus with respect to GDP. CAY stands for an absorption deficit/surplus, domestic demand conditions (real expenditures) and eventually expenditure-reducing policies.

Manufacturing exports (XS)

The export values are fob-values measured in millions of Pesos of 1986. The exports registered in millions of US dollars have to be translated into real terms according to the following formula:

$XS = (EX*e/DEX)*100$

with

XS = real manufacturing exports in millions of Pesos of 1986

EX = nominal manufacturing exports in millions of US-$

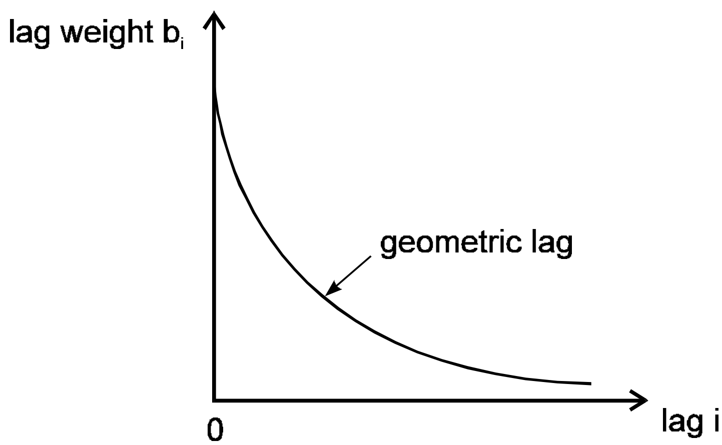
e = nominal exchange rate between Chilean Peso and US-$

DEX = Peso deflator for manufacturing exports with 1986=100

Appendix 2:

Figure 1:

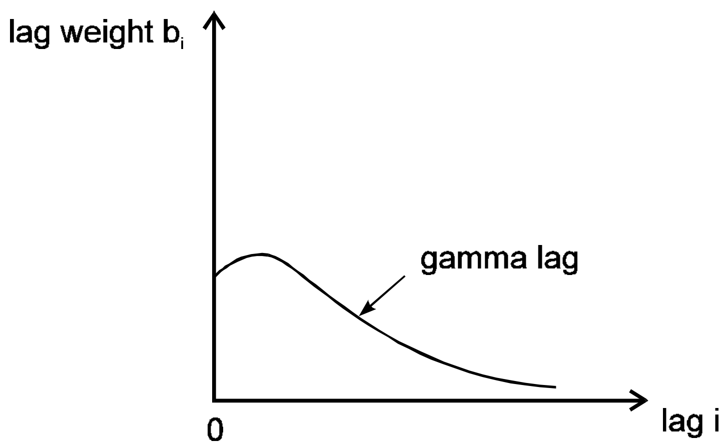
The geometric lag distribution



Appendix 3:

Figure 2:

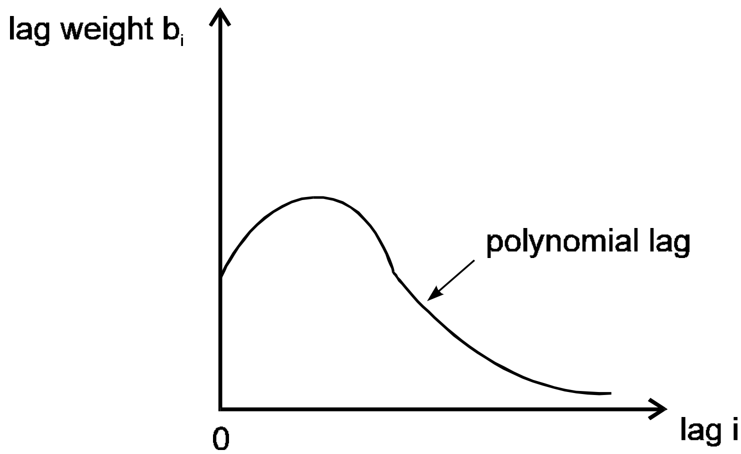
The Gamma lag distribution



Appendix 4:

Figure 3:

The polynomial (second degree) lag distribution



[1] Data cover the period of 1960 to 1996, but should be sufficient for the econometric modelling.

[2] General information on the construction of macroeconomic export models can be found in studies of J. de Gregorio (1984a and 1984b), M. Goldstein and M. Khan (1978), M. Khan (1974), L. Sjaastad (1981), J. Salas (1982), R. Penaloza Webb (1988), M. Khan and M. Knight (1988), F. Nowak (1989), F. Nowak-Lehmann D. (1989), Beenstock et al.(1994), R. Faini (1994), V. Muscatelli et al. (1995), J. Newman et al. (1995), J. Ceglowski (1997) and L. Moreno (1997).

[3] When the impact of RER, DY and CAY is non-separable (in statistical terms), then RER, DY and CAY will enter the regression equation in a multiplicative way. When the impact of the independent variables is separable, they will enter the regression equation in an additive way.

[4] a is the constant and d belongs to the variable CAY that can not be entered as a LOG-value because it can take on negative values (income-absorption deficit) for which the LOG is not defined.

[5] The data for 1996 (and sometimes for earlier years) are preliminary data. They are estimates which are based on the available knowledge of the development of the first half of 1996 (or some quarters before that date).

[6] The transfer function model unlike the geometric lag, Gamma lag and polynomial lag models, is not presumptive in form (see figures 1 to 3).

[7] There also exists a moving average form (MA form) of the model. The latter is more robust to misspecification of autocorrelation of the disturbance, but requires the use of non-linear least squares (Greene 1993, pp.528-529).

[8] If autocorrelation is not corrected, the OLS-estimators will not only be biased, but will not even be consistent (Kelejian and Oates 1981, p. 160).

[9] $grerz_t$ (gamma lag transformed „rerz“) is generated by a manipulation which is completely analogous to the one done in the geometric lag model (Schmidt 1974, p. 247).

[10] h_t is asymptotically negligible. Therefore, its omission will not affect the asymptotic properties of the resulting estimates (Schmidt 1974, p.248).

[11] This procedure is also available under EViews and leads to consistent estimates. EViews allows the user to indicate starting values for g and l (e.g. 0.5 for each of them) and to indicate the maximum number of iterations (EViews 4 User's Guide 2000, pp. 283-285).

[12] See Jenkins' detailed presentation of the transfer function model (1979, pp. 38-66).

[13] The transfer function model requires information on the number of parameters that should enter the numerator and the denominator of the transfer function.

[14] One should be aware of the problem of „over-parametrization“ which can lead to insignifant and rather poor results. This issue was discussed with Dave Reilly from AUTOBOX, P.O. Box 563, Hatboro, PA 19040, U.S.A. AUTOBOX is a software that allows automated time series analysis and is a program that is able to estimate transfer function models. This ability has not been verified and tested by the author because Autobox is a quite expensive, though powerful program.

[15] The assumption of consistency goes back to Mann and Wald (1943) who deducted that under certain conditions, ordinary, linear least squares estimation and inference procedures were valid asymptotically Greene (1993, p.540).

[16] The main problem when variables have to be calculated in real terms is to find the proper base year and the proper deflators. Generally the base year has to be a 'normal' year with no obvious internal and external disequilibria. For Chile's data set ranging from 1960 to 1996 the year 1986 was considered as base year.

[17] The Hausman test could not be performed for the transfer function model.

[18] In September 1973 the military regime under A. Pinochet took over. It is assumed that starting in 1974 a structural change in the economy (change in the structure of the economic models to be applied) might have taken place. It should be noted that the change in the macroeconomic variables that undoubtedly occurred cannot be considered as structural change per se.

[19] This result is not surprising because the procedure used to generate stationary time series can also be used for correcting autocorrelation. Therefore, in a sense the model has been corrected for autocorrelation at the same time that the time series have been made stationary.

[20] AUTOBOX is able to handle transfer functions, however not without shortcomings (Autobox' output is difficult to interpret because Autobox' approach to deal with data totally differs from widely used statistical/econometric software programs; over-parametrization of the models can lead to strange results...). Besides, EViews' programming chief (Chris Wilkins) works on fixing the current problems concerning ARMAX-models.

[21] It was confirmed by AUTOBOX (Dave Reilly) that the EViews results would be very similar to the AUTOBOX results.

[22] These results are consistent with the export supply elasticity results obtained by Newman et al. (1995) and Diewert and Morrison (1988) in static models.

[23] When real income (gdpz) instead of trend income (dyz) was used, cayz was statistically significant in all four distributed lag models. This suggests that exports will cease to be dependent on the income-absorption gap if exporters make long-run investment decisions (inclusion of trend income (dyz) instead of current real income (gdpz)).

[24] The Argentinian peso was fixed with respect to the US-dollar at the ratio 1:1.

[25] The Chilean peso was pegged to a currency-basket consisting of the US-dollar (45%), the German mark (30%) and the Japanese yen (25%).The exchange rate band was set to be +/-10% (Banco Central de Chile, Memoria Anual 1995, pp.13-14 and p. 33).

[26] The regression coefficients would change signs from one quarter to the other.

[27] Transfer function models are so advantageous because they are able to shape the lag structure corresponding to the data and their cross correlations. The cross correlations hinted at a polynomial lag structure which can of course be easily modelled by a transfer function.

[28] DW_{geo}= 1.99; DW_{gam}= 1.50; DW_{poly}= 1.49; DW_{trans}= 1.96

[29] The results shown in tables 4 were obtained by using OLS/TSLS starting values and less parameters, relying on EViews as a second best program.

[30] If income-absorption > 0, we talk about an absorption deficit (depressed demand conditions) and if income-absorption < 0, we talk about an absorption surplus.