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Do Norwegian Firms Form Exptrapolative Expectations?

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Abstract:
The hypothesis of extrapolative expectations is tested directly using Norwegian microeconomic data on firms' expectations of the prices of own products in domestic and export markets and expectations of demand for own products in domestic and export markets. The data, which are categorical, are taken from a survey of firms in manufacturing and mining. Different versions of extrapolative models are discussed, i.e. the general extrapolative model, the pure adaptive scheme and the error-learning model. The data are analyzed by means of different measures of association in cross-tables and loglinear probability models. Because of the sample size and the distribution of observations through out the table, statistical conclusions cannot be drawn for the hypothesis of adaptive expectations. For this version of extrapolative expectations, only descriptive measures are provided. Our empirical results support a general version of extrapolative expectations. The restrictions on the lag structure which take us from the general version to the model of adaptive expectations do, when confronted with our data, seem to be too restrictive.

Keywords: Extrapolative Expectations, Microeconomic Data, Tendency Surveys

JEL classification: C21, C42, D84

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1. Introduction and Summary

Expectations on how different prices and quantities will evolve, are seen as crucial to how the economy functions. Different hypothesis of how these expectations are formed have been launched in the economic literature. The main distinction is between rational and extrapolative expectations. In this paper different versions of extrapolative mechanisms are analyzed by use of observed expectations held by Norwegian firms, concerning prices and demand for the firms' products in domestic and export markets.

According to the extrapolative model, agents form their expectations of a variable as a function of the variable's history as observed by the agents. Different types of extrapolative expectations have been proposed, out of which the adaptive expectations hyopthesis is the most familiar. In this paper special attention is paid to the general extrapolative model, which encompasses all types of extrapolative expectations, and to the adaptive model and the error-learning model which is a special case of the adaptive one. The adaptive expectation hypothesis was first proposed by Fisher (1930), but later developed by Cagan (1956) and Nerlove (1958).

Because data on expectations seldom are available, most empirical studies of how expectations are formed are based on the indirect approach in which the expectations hypothesis are combined with a specific economic theory. Parameter restrictions derived from the joint hypothesis are typically tested by use of time series. This creates an identification problem because it is often not possible to tell whether the resulting reduced form equations are derived from adaptive expectations or from a partial adjustment mechanism. If the variable that expectations are related to, evolve according to an extrapolative scheme, the hypothesis of rational expectations may also lead to the same reduced form equations as the adaptive expectations hypothesis.

In this study the direct approach to testing the formation of expectations is applied. Direct observations of firms' expectations is available from a quarterly survey conducted by Statistics Norway. The variables in the survey are categorical; the firms are asked whether they expect prices or demand to increase, decrease or remain stable. Corresponding questions are posed related to the most recent changes observed by the firms. No quantitative information is collected. No attempt has been made to transform the data into quantitative estimates when the data are analyzed. The methodological approach is thus in line with former empirical studies of expectations by Kawasaki and Zimmermann (1986), König, Nerlove and Oudiz (1981), Nerlove (1983), Stålhammar (1988) and Zimmermann (1986) (the studies are surveyed in Svendsen (1993a)).

Different measures of association in cross-tables and loglinear probability models have been used. The applied measures require a certain sample size and distribution of observations through out the table, if statistical conclusions are to be drawn. These requirements are not met by my data in the case of the adaptive expectations hypothesis. For this model only descriptive measures are therefore presented.

The survey data from Statistics Norway have been analyzed in the light of the hypotesis of rational expectations in a former paper (Svendsen (1993b)). The results reject the hypothesis of rational expectations. The results indicate some sort of a regressive mechanism for the demand variables; the firms expect the demand to return to some sort of a "normal level".

The results presented in this paper give support to some sort of extrapolative mechanism for the price variables and the demand on export markets. The adaptive expectation model does seem to be too restrictive. Again, it may look like regressive expectations may explain the observed expectations of demand on domestic markets.

My finding on expectations are in line with the existing empirical literature on how expectations are formed. The accumulated evidence does not give a much support to the rational expectations hypothesis. Most studies conclude that extrapolative, and quite often adaptive, expectations do better in explaining the observed expectations. This literature is surveyed in Maddala (1991) and Svendsen (1993a).

2. Extrapolative models - quantative data

This section presents different ways of modelling extrapolative expectations. Let y_t be the realization of a stochastic variable in period t. The value y_t is important for the outcome of the agents' decisions made in period t-f but yet unknown. The i'th agent instead replaces y_t by its expectation of y_t seen from f periods in advance; ${}_{t\text{-}f}y_{i,t}{}^{e}$. For expository reasons we set f equal to 1, and supress the subscript indicating the period in which the expectations are formed and the one indicating what agent the expectations corresponds to. The agents' expectations are not to be confused with the objective mathematical expectations. The general form of an extrapolative expectations model is given in (1). v_t is an error term with white noise properties.

(1) $$y_t^e = \beta_1 y_{t-1} + \beta_2 y_{t-2} + \ldots + \beta_n y_{t-n} + v_t, \quad n \leq \infty$$

A variety of extrapolative models may be derived if one assumes different kinds of restrictions on the number of lags and on the ß's. Different types of extrapolative models may be tested within the general framework if the data do not reject the general form in (1). The maintained hypothesis is then the general form expressed in (1).

(2) $$y_t^e = y_{t-1} + v_t''$$

The static expectation model is shown in (2). Here the number of lags are restricted to one, with the coefficient on this lag equal to one. Hence the expectation of a future value of y is assumed to equal its latest observed value up to a stochastic error term, v_t''.

Another version of the extrapolative model is derived by setting n=2 and restricting the sum of β_1 and β_2 to be equal to one.

(3) $$y_t^e = \beta_1 y_{t-1} + (1 - \beta_1) y_{t-2} + v_t''' \Rightarrow y_t^e - y_{t-1} = -(1 - \beta_1)\Delta y_{t-1} + v_t'''$$

The expectations in (3) are expressed as a finite distributed lag in the two past observations. (3) is known as the "bandwagon"-model when $\beta_1 > 2$. In this case agents expect the rate of increase from the current to the next period to be larger than between the two last periods. Such an expectation mechanism may be destabilizing if expectations are selv-fullfilling. The agents are expecting the opposite direction of change if $\beta_1 < 1$.

The most commonly used version of extrapolative expectations is the adaptive expectations model. There are several ways of expressing this model. The version given in (4) is called the pure adaptive scheme. ϵ_t is a stochastic error term with white noise properties.

(4) $$y_t^e = \delta y_{t-1} + \tau y_{t-1}^e + \epsilon_t, \quad \delta + \tau = 1$$

The pure adaptive scheme shows the expectations as a weighted average of the last observation (y_{t-1}) and the previous held expectations (y_{t-1}^e). We cannot, as will be discussed later, test the parameter restriction in (4) if data are categorical. The parallel to the general extrapolative model is easily found by solving for y_t^e in (4):

(5) $$y_t^e = \delta \sum_{j=0}^{\infty} (1 - \delta)^j y_{t-j-1} + \sum_{j=0}^{\infty} (1 - \delta)^j \epsilon_{t-j}$$
$$n = \infty \wedge \beta_j = \delta(1 - \delta)^j$$

(5) is an infinite lag-distribution in lagged realizations with geometrical declining weights.The weights decline with increasing distance in time and the weight placed on the most recent observation increases with δ. The model by which the expectations are formed is characterized by a short memory if δ is close to one and by a long memory if δ is close to zero.

According to the adaptive expectations hypothesis agents adjust their previous expectations in accordance with the prediction error made in the most recent period (y_{t-1} - y_{t-1}^e). This is clearly seen if we rewrite the pure adaptive scheme using the restriction on the sum of δ and τ, giving rise to yet another version of the model, called the error-learning model.

(6) $$y_t^e - y_{t-1}^e = \delta(y_{t-1} - y_{t-1}^e) + \epsilon_t, \quad 0 < \delta < 1$$

Because the adaptive expectations model is the one most widely used, most of the criticism against the extrapolative models are in connection with this model. One of the main weaknesses of the adaptive and other extrapolative models is that they allow agents to make systematic errors over time. In a period of increasing (decreasing) prices, price expectations made in accordance to the adaptive expectations model will systematically underestimate (overestimate) future prices. Another important point of criticism towards the use of extrapolative models, is the absence of other sources of information included in the information set. Additional information could be knowledge about other state or policy variables, and about the economic structure. These two points of critisism are met by the model of rational expectations. In certain situations it may be impossible to identify whether the expectations are made in accordance with the model of extrapolative or rational expectations for instance if the reduced form equation for the variable to be predicted, happens to follow an extrapolative scheme.

The unsatisfying use of information in the extrapolative models, is to some extent remedied by adding other variables to the models. The augmented adaptive model is one such model. The regressive expectations model is yet another variant. The augmented adaptive model is shown in (7) where the model is augmented with K other variabels. Candidates could be variables supposed to be part of the reduced form equation for y_t , but also other variables the agents may have made use of, should be included.

(7) $$y_t^e = \delta' y_{t-1} + (1 - \delta') y_{t-1}^e + \alpha_1 x_{1t} + ... + \alpha_K x_{Kt} + \varphi$$

The adaptive scheme has been criticized for having a too restrictive lag structure when compared to the general extrapolative scheme. The geometrical declining weights need not to be the most efficient way of using historical information. This remark should however be recognized as a part of the general critisism towards extrapolative models, regarding the restrictions put upon the content of the information set and how the information actually is used. The adaptive version of the extrapolative models is more restrictive than the general one, but they do all suffer from inefficient use of available information.

3 Variable construction and the data

Before we continue in establishing the categorical counterparts to the extrapolative models for quantitative data, we need to define some variables and to say some words about our data.

The data analyzed are taken from a quarterly survey conducted by the Statistics Norway[1]. Both the expected and observed directions of change in prices and incoming orders are taken from the survey, giving a set of observations for each firm. All data are categorical, i.e. the firms report only qualitative changes in the form; "prices (incoming orders) are expected to go up / remain unchanged / go down" and "prices (incoming orders) have gone up / remained unchanged / gone down". Incoming orders are used as a proxy for demand towards firms.

Let Y be either the change in prices on domestic or export market, or the change in demand from domestic or export markets. The firms report the observed direction of change in Y from period t-1 to t and the expected direction of change from period t to t+1, at the start of period t. The firms' reports on the direction of change collected ex post may differ from what the direction of change actually have been, partly because the firms may not have all information needed when the data are collected for the survey (in fact 5 days before the end of the previous period (see footnote 1)). The firms opinion regarding the previous direction of change, may be revised as new information is made available. We have, in fact, two observations of the firms' expectations concerning the direction of change from t-1 to t; the ex ante expectations and the ex post expectations. We call the former an expectation and the latter a perception.

We denote the firms' expectations regarding the direction of change from period t-1 to t, reported in period t-1, EY. L^jEY is defined as firms' expectations regarding the direction of change in Y from period t-j-1 to t-j, reported in period t-j-1. We define PY as the firms' perceptions regarding the direction of change in Y from period t-1 to t, reported in period t, and L^jPY (j>1) as the firms' perception of the change from period t-j-1 to t-j, reported at the beginning of period t-j. The four variables are defined over the categories "up", "no change" and "down". We have assigned the value 1 to the category "up", 2 to the category "no change" and 3 to the category "down". EY, L^jEY, PY and L^jPY are respectively functions of the latent variables ${}_{t-1}y_{it}^{e}$, ${}_{t-j-1}y_{i,t-j}^{e}$, y_{it} and $y_{i,t-j}$; variables we do not observe.

According to the hypothesis of extrapolative expectations will firms in period t-1, form their expectations of the variable's movement from t-1 to t by use of their knowledge of the variable's history as gathered up to period t-1. As a proxy for this information, we apply a set that consists of L^jPY, j=1,...,n. This proxy will differ from the variables used by the firms when expectations are

[1] The survey started in 1973.4 and covers firms in mining and manufacturing with more than 100 employees. The number of firms covered by the survey has varied throughout the period. It started out with 470 firms, the number of firms then increased to nearby 700 in 1978, and have since then fallen to around 450 firms by the end of 1990. The main reason for the decrease in the number of firms, is structural changes in the economy. The micro data for the period 1982:2 - 1987:2 are lost. The data is collected at the end of March, June, September and December, with deadline for the firms 5 days before the end of each quarter.

formed, i.e. the perceived changes from period t-j-1 to t-j seen from period t-1, if the firms in light of new information gathered after period t-j have revised their perceptions of the change from period t-j-1 to t-j. We have no information about these variables. At time t-1, LPY (j=1) embodies the most up-dated information firms have concerning the direction of change from period t-2 to t-1. LPY should not be regarded as a proxy when we assume it to be part of the applied information set.

Another variable to be chosen as a proxy for the information set used by firms' is the direction of change between earlier periods calculated from official statistics. We would then have to assume the direction of change being the same for all firms covered by the same sector in official statistics and that firms perceptions of the direction of changes are the same as what can be read from official figures.

We need two more categorical variables, with the values calculated based on the survey. LC, called the correction term, is a function of the latent variable ($y_{i,t-j}-y_{i,t-j}^{e}$) and is defined in equation (8) and in table I. LC indicates the mistake a firm in period t-1 realizes it made when it formed its expectation of the direction of change from t-2 to t-1 (LEY) in the period before. The mistake is known after the firm have decided how to perceive the actual change (LPY) from t-2 to t-1. LC is defined over the categories "underestimated", "correctly estimated" and "overestimatied". The categories are respectively assigned the values 1, 2 and 3.

(8)
$$LC = LPY - LEY \begin{cases} < 0 & \rightarrow \quad \textit{'underestimated'} \\ = 0 & \rightarrow \quad \textit{'correctly estimated'} \\ > 0 & \rightarrow \quad \textit{'overestimated'} \end{cases}$$

Table I: Categories of LC for different combinations of LEY and LPY. UN=underestimated, CO=correctly estimated and OV=overestimated.

		LPY		
		up (1)	no change (2)	down (3)
	up (1)	CO	OV	OV
LEY	no change (2)	UN	CO	OV
	down (3)	UN	UN	CO

The revision term, R, is a function of the latent variable (${}_{t-1}y_{i,t}^{e}- {}_{t-2}y_{i,t-1}^{e}$). R indicates in which direction the expectation made in period t-1 of the direction of change in Y from period t-1 to t is revised related to the expectation made in period t-2 of the direction of change from t-2 to t-1. Ris defined in equation (9) and in table II over the categories "upward revision", "no revision" and downward revision", respectively assigned the values 1, 2 and 3.

(9)

$$R = EY - LEY \begin{cases} < 0 & \Rightarrow \quad \textit{'upward revision'} \\ = 0 & \Rightarrow \quad \textit{'no revision'} \\ > 0 & \Rightarrow \quad \textit{'downward revision'} \end{cases}$$

Table II: Categories of R for different combinations of EY and LEY. The values assigned to the categories in parantheses.

		EY		
		up (1)	no change (2)	down (3)
	up (1)	no rev. (2)	downward rev. (3)	downward rev. (3
LEY	no change (2)	upward rev. (1)	no rev. (2)	downward rev. (3)
	down (3)	upward rev. (1)	upward rev. (1)	no rev. (2)

4 Categorical versions of the extrapolative models

In what follows we will present the categorical counterparts of the extrapolative models presented in section 2. The models in this section are not derived in a strong logical sense from the models in section 2, but are interpretations of them in the light of categorical variables. Some of the categorical versions cover more than one quantitative version, others are less restrictive than their quantitative counterpart.

When we analyze various extrapolative expectations mechanisms by use of categorical data, the analysis can be carried out by studying the association between different sets of variables in cross-tables. We apply different types of loglinear probability models and measures of association. The different statistical measures applied to the data will be presented in later sections.

We assume an association to be present between expectations and former realizations of the variable in the general extrapolative model (equation (1)). In a categorical frame-work this can be interpreted as studying the patterns of association in a multi-variate cross-table formed from the variables included in brackets in (10).

(10)

The general extrapolative model: [$EY, LPY, L^2PY, L^3PY, ..., L^nPY$]

H_0: *No association between EY and* L^jPY, $j=1,...,n$

H_1: *Association between EY and* L^jPY, $j=1,...,n$

H_1 may arise from an extrapolative expectation mechanism, while H_0 is "some other mechanisms". If H_0 is rejected for at least one lag of the variable, we will take this as support for some sort of extrapolative expectations.

Equation (11) is the categorical interpretation of both the model of static expectations (equation (2)) and a general extrapolative model in only one lag.

General extrapolative in one lag, Static expectations: *[EY, LPY]*

(11) H_0: *No association between EY and LPY*

H_1^a: *Association between EY and LPY*

H_1^b: *Perfect, positive association between EY and LPY*

Two alternative hypothesis may be formulated in relation to (11), the first (H_1^a) being the general extrapolative model with only one lag. The second one (H_1^b) is nested within the first one and represent the model of static expectations. Both are nested within the alternative hypothesis connected to (10). Perfect association means a correlation coefficient equal to one.

If we set the number of lags equal to two and restrict the sum of the parameters to be equal to one, we get the finite distributed lag model in (3), known as the "bandwagon" -model if $\beta_1 > 2$. A categorical interpretation of the finite distributed lag model is given in (12).

***The finite distributed lag model:* [*EY, LPY,* L^2PY]**

(12) **H_0: *No association between EY and* L^jPY, $j=1,2$**

H_1: *Association between EY and* L^jPY, $j=1,2$

We cannot, within the framework of categorical data, impose or test the parameter restrictions on the general extrapolative model which in the quantitative version lead to the finite distributed lag model. The model in (12) does then cover both the model in (3) and a general extrapolative model in two lags. The sign on an eventual association between the variables in (12) can rule out some cases. The "bandwagon"-model implies that the association between EY and LPY is positive and between EY and L^2PY to be negative. So, if both association terms show up to be positive, we can rule out the "bandwagon"-model. Another way to model the finite distributed lag model with categorical data, is to construct two new categorical variables (EY - LPY) and (LPY - L^2PY) according to the alternative formulation in (3).

The basis for testing the adaptive expectations is the pure adaptive scheme (4) or the error-learning model (6). The categorical interpretations of these two models are shown in (13) and (13).

Adaptive expectations: [*EY, LPY, LEY*]

(13) ***H_0: No association between EY and LPY or between EY and LEY***
H_1: Positive association between EY and LPY and between EY and LEY

The error–learning model: [*R, LC*]

(14) ***H_0: No association between R and LC***
H_1: Positive association between R and LC

The parameter restriction on the sum of δ and τ in the pure adaptive scheme is taken as an assumption when we go from the pure adaptive scheme (4) to the error-learning model (6). The restriction can be tested empirically if quantitative data are available. This is, however, not possible with categorical data. The categorical interpretation of adaptive expectations (13) is derived without the use of the parameter restriction while the categorical interpretation of the error-learning model (13) is derived by use of it. The two-dimensional cross-table of R by LC is in fact an aggregation, using the parameter restriction, over the three-dimensional cross-table of EY, LPY and LEY. So, while the pure adaptive scheme in (4), subject to the restriction on δ and τ, is identical to the error-learning model in (6), their categorical intepretations in (13) and (13) may differ.

However, even though the parameter restriction cannot be tested by use of categorical data, the degree of association between EY and LPY, respective EY and LEY in the categorical interpretation of adaptive expectations can tell us something about the weight placed on the latest observations. If the association between EY and LPY are higher then between EY and LEY, this indicates the expectations to be rather myopic. If the association between EY and LEY in addition is non-significant, the model is reduced to the static model in (11). The opposite case, with a non-significant association between EY and LPY and a positive association between EY and LEY, indicates a rather naive expectations model with the expectations made in one period being equal to the expectations made in the preceding period.

In the categorical interpretation of the error-learning model, a high positive association between R and LC indicates that heavy weight is placed on the most recent observations. A warning has to be mentioned when interpreting results from (13). The two variables in the model are derived as the differences between LPY and LEY, and between EY and LEY. Hence LEY are included in both variables. This may lead to a positive association between R and LC, even if there are no or negative association between one or both couples in (13).

We also mentioned the augmented extrapolative model (7) and the regressive model in section 2, but will not analyze these models in the present paper. A general categorical version of the augmented one is however shown in (15). X_1 to X_H represent different variables that are supposed to explain the realization of Y.

(15)

The augmented extrapolative model: *[EY, LPY, LEY, X_h], h=1,...,H*

H_0: No association between EY and LPY , between EY and LEY or between EY and X_h

H_1: Positive association between EY and LPY , between EY and LEY and between EY and X_h

5 Measures of association and loglinear probability models

The models presented in section 4 give rise to cross-tables with different dimensions. The general extrapolative model is of dimension n, the adaptive model and the finite distributed lag model are both three-dimensional, while the static expectations model and the error-learning model are two-dimensional. The different hypothesis can be tested by use of measures of association or formulated as restrictions on the parameters in loglinear probability models. For a general reference to loglinear probability models and measures of association see Bishop, Fienberg and Holland (1975) or Fienberg (1980). Unfortunately, because of too few observations and an unequal distributions of the observations throughout the tables, the distributional properties of the different tests fail to hold when we deal with cross-tables of dimension three or higher[2]. In some periods we are not able to estimate the models at all.

Accordingly, we are not able to test the general extrapolative model. We have however, analyzed the model with only one lag included at a time. The interaction between firms' expectations (EY) and four different lags (the first, second, third and fourth) of the realization of the variable (LPY) have been studied partially. Because our data does not allow us to include more than one lag at the time, we can not study the interaction controlled for the influence of other lags. The model is analyzed by use of the Likelihood ratio test and the Goodman and Kruskal's gamma (to be described). The results must be interpreted in accordance to these remarks.

Statistics have been calculated for the adaptive model despite few observations and an unequal distribution of data. However, no formal tests have been carried out and the statistics should be treated as descriptive measures. The measures are the Likelihood ratio statistics and deviations between parameters in a loglinear probability model. These latter will be described in section 5.2.

There are no formal problems related to the tests of the static and the error-learning models. The static expectations model will be considered when studying the association between the expectations and the first lag of the realization within the general extrapolative model. The loglinear models applied to the error-learning mode in addition to the Likelihood ratio statistics and the Goodman and Kruskal's gamma, are described in section 5.3. The augmented adaptive model needs at least a four dimensional table and have not been tested in this paper.

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[2] An outcome is defined as the combination of scores a firm have on a set of variables. In a S-dimensional cross-table where each of the S varaibles can take on three different categories, the number of possible outcomes is 3^S. A thumb-finger rule is that at least 80 percent of the combinations should have expected frequencies exceeding 5 and none should have expected frequencies less then one, for the distributional properties of measures as the Likelihood ratio test to hold. It is also necessary that there are none zeros in the marginal tables for the model to be estimable.

5.1 The general extrapolative model

The general extrapolative model is tested by use of the Likelihood ratio statistics and the Goodman and Kruskal's gamma. These two measures, commonly used in the literature and frequently used in this paper, are defined in this section.

We test the null-hypothesis of independence (no association) between two or more variables in a cross-table against the alternative hypothesis of association in most of our tests. The Likelihood ratio (X^2) statistics is one of many measures that is based upon the discrepancies between the expected cell counts in a cross-table, given the assumption of no association, and the observed ones. Let n_{pm} be the number of observations in the (p,m)'th cell of a 3x3 cross tabel where p (p=1,..,P) represents the category on the row variable and m (m=1,..,M) the category on the column variable and let $\hat{n}_{pm}$ be the expected number of observations under the null hypothesis. Then the formulae for the X^2 statistics under H_0 is given in (15).

(16)
$$X^2 = 2\sum_{p=1}^{p=P} \sum_{m=1}^{m=M} n_{pm} \log\left(\frac{n_{pm}}{\hat{n}_{pm}}\right)$$

The formulae for $\hat{n}_{pm}$ in the case of no association (H_0) is given in (17). Here $n_{p.}$ and $n_{.m}$ are the marginal distributions (the number of observations of the p'th and the m'th category of respectively the row and the column variable) and $n_{..}$ is the total number of observations.

(17)
$$\hat{n}_{pm} = \frac{n_{p.}\, n_{.m}}{n_{..}}$$

The X^2-statistic follows an asymptotic χ^2-distribution with (P-1)(M-1) degrees of freedom and the null hypothesis is rejected for high, positive values on the observed X^2.

Our variables are ordinal, i.e. the orderings of the categories can be given a meaningful interpretation as "prices go up" represents a higher increase in prices than "prices remain unchanged" or "prices go down". A typical nominal categorical variable would be a variable indicating which sector a firm belongs to. When we deal with ordinal categorical data, we do not only ask whether an association is present or not, but we would also like to know in which direction an eventual association goes. In the general extrapolative model, for instance, we would expect the association to be positive so that firms after having observed an increase expect (LPY=1) the variable to continue to increase (EY=1).

Only nominal association can be tested for by use of a X^2-test. There are several statistics available if one wants to test for ordinal association. We will present results based on the Goodman-Kruskal 's gamma (GKG) (Goodman and Kruskal (1979)). We have two drawings from the total sample. We define PS as the probability for the two drawings being equally ordered[3], PD the probability for them being unequally ordered, while PT is the probability for one or both variables having the same values in both drawings. We note that PS+PD+PT=1. The conditional probabilities for equally or unequally ordered, are respecively PS/(1-PT) and PD/(1-PT). The GKG is defined as the

[3] Let {i,j} and {i',j'} be the outcomes of two drawings from the total sample. Then, the two drawings are equally ordered (cf. PS) if {i>i' and j>j'} or {i<i' and j<j'}, unequally ordered if {i>i' and j<j'} or {i<i' and j>j'} (cf. PD), while they have the same values in both drawings if {i=i' and/or j=j'} (cf.PT).

difference between these two conditional probabilities and is used as a measure of ordinal association.

(18)
$$GKG = \frac{PS}{1-PT} - \frac{PD}{1-PT} = \frac{PS-PD}{PS+PD}$$

GKG varies between -1 and 1, -1 with perfect negative association and 1 with perfect positive association. In the case of no association, GKG equals zero. We test the hypothesis of no association by use of a t-test. One disadvantage with measures of ordinal association, is that they can only reveal monotonic association, i.e. the direction of association is the same for all subtables of the entire cross-table.

5.2 Adaptive expectations

In the model of adaptive expectations presented in section 4, three variables are included; EY, LEY and LPY. The patterns of association in this model can be investigated by use of a 3-dimensional loglinear probability model.

Let p, m, and q (p,m,q=1,2,3) denote the categories on EY, LPY and LEY, respectively. We define a simultaneous event {p,m,q} as EY=p, LPY=m and LEY=q. $\pi_{pmq}^{EY,LPY,LEY}$ is the probability for the event {p,m,q} to occur. This probablity can be modeled in a loglinear probability model in order to separate the effects from the three marginal distributions (EY, LPY and LEY), the simultaneous distribution within the three pair of variables (EY*LPY, EY*LEY and LPY*LEY) and from the simultaneous interaction between all three variables. Model I shows a saturated[4] loglinear probability model for three categorical variables, EY, LPYand LEY.

(19)
$$\text{MODEL I:}\quad \log(\pi_{pmq}^{EY,LPY,LEY}) = \mu_I + u_p^{EY} + u_m^{LPY} + u_q^{LEY} + u_{pm}^{EY,LPY} + u_{pq}^{EY,LEY} + u_{mq}^{LPY,LEY} + u_{pmq}^{EY,LPY,LEY}$$

The main effects of EY, LPY and LEY, say u_p^{EY}, u_m^{LPY} and u_q^{LEY} represent the departure of the log-probability from the average of the log-probabilities, say μ_I, due to the observed category on EY, respective LPY or LEY. The bivariate interaction parameters, say $u_{pm}^{EY,LPY}$, $u_{pq}^{EY,LEY}$ and $u_{mq}^{LPY,LEY}$, capture the departure from the sum of the average μ_I and the main effects u_p^{EY}, u_m^{LPY} and u_q^{LPY}, due to the observed association between EY and LPY, EY and LEY and LPY and LEY. The model also includes a set of trivariate interaction parameters ($u_{pmq}^{EY,LPY,LEY}$), capturing the impact on the log-probability from the simultaneous distribution of all three variables. The trivariate interaction parameters are to be included only if all three sets of bivariate interaction parameters are included, due to the model being hierarchic. The constant μ_I, is derieved from the requirments on the sum of the estimated probabilities. A positive value on one of the effect parameters describing the probability for the event {p,m,q}, increases the probability for the event to occur, while a negative

[4] In a saturated loglinear probability model the number of degrees of freedom is zero, and the observed frequencies of the event {p,m,q} will equal those calculated by use of the estimated parameters from the loglinear probability model.

value reduces the probability[5]. In the case of no association between two of the variables, the respective bivariate interaction parameters and the trivariate interaction parameters will all equal zero.
According to the hypothesis of adaptive expectations, association will be present between EY and LEY and between EY and LPY in (19). The adaptive model is our alternative hypothesis and we formulate the null hypothesis as $u_{pm}^{EY,LEY} = u_{pmq}^{EY,LPY,LEY} = 0$ and $u_{pm}^{EY,LPY} = u_{pmq}^{EY,LPY,LEY} = 0$. The two sets of restrictions are tested by use of a Likelihood ratio test. When we analyze the patterns of bivariate interaction within the trivariate model, we control for the effect from the third variable.

Model I should be the preferred one when studying the adaptive expectations model. But because of too few observations and an unequal distribution of the observations throughout the tables in our data, the distributional properties of the different available tests, as the Likelihood ratio test, fail to hold. Even worse, we are not able to estimate the model in all periods. We have considered to combine categories or to exclude combinations with few observations in order to solve these problems. This is problematic however, since we by then reduce the variation in our data.

The adaptive model is estimated including all three variables for those periods with none zeros in the marginals. The number of periods for which the model could be estimated increases when we exclude the trivariate interaction parameter from the model. This restriction is imposed during estimation. All results, as for instance the observed Likelihood ratios, must be viewed just as descriptive measures. Because of the shortcomings of our data, we can not draw conclusions regarding the significance of whether the different configurations can be set equal to zero.

In addition to the Likelihood ratios, we report a set of parameters, $\lambda_{pp'm}$ and $\lambda_{pp'q}$, defined in (20).

$$\text{(20)} \qquad \lambda_{pp'}^{EY} = u_p^{EY} - u_{p'}^{EY}, \qquad \lambda_{pp'm}^{EY,LPY} = u_{pm}^{EY,LPY} - u_{p'm}^{EY,LPY}, \qquad \lambda_{pp'q}^{EY,LEY} = u_{pq}^{EY,LEY} - u_{p'q}^{EY,LEY}$$

We can express the odds ratio between EY=p and EY=p' (p≠p'), given the category on the two other, LPY and LEY, by the λ's:

$$\text{(21)} \qquad \log\left(\frac{\pi_{pmq}^{EY,LPY,LEY}}{\pi_{p'mq}^{EY,LPY,LEY}}\right) = u_p^{EY} - u_{p'}^{EY} + u_{pm}^{EY,LPY} - u_{p'm}^{EY,LPY} + u_{pq}^{EY,LEY} - u_{p'q}^{EY,LEY}$$

$$= \lambda_{pp'}^{EY} + \lambda_{pp'm}^{EY,LPY} + \lambda_{pp'q}^{EY,LEY}$$

On the right-hand side in (21) the ratio is explained as a function of the difference in main effects ($\lambda_{pp'}$) and in the bivariate effects ($\lambda_{pp'm}$ and $\lambda_{pp'q}$), due to changing the category on EY. A positive value on one of the λ's increases the probability for EY=p relative to the probability for EY=p'.

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[5] The number of parameters in model I are 64, while we have only 26 independent equations. During estimation restrictions are put on the sum of the different sets of parameters and on the sum of the π_{pmq}'s, leaving us with 26 freely estimated parameters. The restrictions are:

$$\sum_{i\in(p,m,q)} u_i = \sum_{i\in(p,m)} u_{pm} = \sum_{i\in(p,q)} u_{pq} = \sum_{i\in(m,q)} u_{mq} = \sum_{i\in(p,m,q)} u_{pmq} = 0, \quad \sum_{p=1}^{p=3}\sum_{m=1}^{m=3}\sum_{q=1}^{q=3} \pi_{pmq} = 1$$

From the hypothesis of adaptive expectations, we can deduce restrictions on the sign of some of the λ's describing the bivariate interaction. That is the reason why we are studying the λ's instead of the bivariate interaction parameters in (19). The interesting λ's for the interaction between EY and LPY are defined below. The same set of λ's can be defined for the interaction between the expectations and the previous held expectations (EY,LEY).

$$\text{(22)} \quad \begin{array}{lll} \lambda_{121}^{EY,LPY} = u_{11}^{EY,LPY} - u_{21}^{EY,LPY}, & \lambda_{212}^{EY,LPY} = u_{22}^{EY,LPY} - u_{12}^{EY,LPY}, & \lambda_{313}^{EY,LPY} = u_{33}^{EY,LPY} - u_{13}^{EY,LPY}, \\ \lambda_{131}^{EY,LPY} = u_{11}^{EY,LPY} - u_{31}^{EY,LPY}, & \lambda_{232}^{EY,LPY} = u_{22}^{EY,LPY} - u_{32}^{EY,LPY}, & \lambda_{323}^{EY,LPY} = u_{33}^{EY,LPY} - u_{23}^{EY,LPY} \end{array}$$

The model of adaptive expectations restricts all six parameters defined in (22) to be positive. A positive sign on one of the parameters means that the probability for expecting (EY) the prices (or demand) to move in the same direction (up, unchanged or down) as observed (LPY), or expected (LEY), between the two last periods, is higher than expecting the variable to move in another direction than observed or expected before. As the λ's are derived from the parameters in the trivariate loglinear model, we controll for the third variable when studying the bivariate interaction between the other two variables in the adaptive model. It has to be stressed that the purpose of reporting the λ's are just for describing the interaction patterns. No statistical inferences can be made.

5.3 The error-learning model

If the error-learning model is supported by our data, we should expect to find a significant association between the two variables; R and LC. In addition, the association should be positive according to the values we have assigned the categories on R and LC. If the direction of change was correctly estimated last period (LC=2), no revision (R=2) should be made. If the direction of change was underestimated (LC=1), an upward revision (R=1) should take place, and a downward revision (R=3) if confronted with an overestimation (LC=3).

A remark has to be made before we continue. Because of the categorical nature of our data, we are not able to capture all quantitative cases of over- or underestimation and the following revisions that are made. According to the quantitative version of the error-learning model should a firm make a downward revision in its expectations and expect an increase from t to t+1 by something between 3 and 10 percent, if the firm expected prices to increase by 10 percent from period t-1 to t, and at the beginning of period t have perceived that prices actually have increased, but by only 3 percent. Using categorical data, what we observe is a firm wich first expectes an increase from t-1 to t, and then at period t perceives an increase (LC=2) to have taken place and if the error-learning model is supported, consequently expectes the prices to continue to increase from t to t+1 (R=2).

The error-learning model is tested by use of two-dimensional loglinear probability models. Three different models have been considered during estimation; a standard loglinear probability model for nominal categorical data and two loglinear probability models for ordinal categorical data. In the latter ones, the ordinal nature of our data have been made use of in order to capture the pattern of association between the two variables in as few parameters as possible. These models also allow us to test for ordinal association. The three different models are to be presented in this section. For each the null of no association can be tested. For a general reference to ordinal loglinear probabilty models see Agresti (1984).

Model II shows a saturated loglinear probability model for two categorical variables, R and LC. We let r denote the category on R and k the category on LC (r,k=1,2,3). $\pi_{rk}^{R,LC}$ is the probability for the simultaneous event {r,k}, defined as R=r and LC=k, to occur.

$$(23) \qquad MODEL\ II:\ \log(\pi_{rk}^{R,LC}) = \mu_{II} + u_r^{R} + u_k^{LC} + u_{rk}^{R,LC}$$

The interpretation of the constant μ_{II}, the main effects, u_r^R and u_k^{LC}, and the bivariate interaction parameters, $u_{rk}^{R,LC}$, are similar to those of model I. In the case of no association between R and LC the bivariate interaction parameters will all equal zero. A LR-test similar to the one shown in (15) is identical to testing the restriction $u_{rk}^{R,LC} = 0$ (for all r,k).

As already mentioned in section 4, the two-dimensional cross-table of R by LC is an aggregation of the three-dimensional cross-table of EY, LPY and LEY. The parameters in model II can thus be shown to be non-linear functions of the parameters in model I. In principle, it should be possible to test the restrictions imposed upon the three-dimensional cross-table when going from equation (19) to equation (22). Because of the non-linearities, however, we have not been able to derive testable restrictions.

Within the framework of model II, no information is given about the direction of an eventual association. In addition we are left with 9 parameters describing the bivariate interaction (out of which only 4 are freely estimated), a rather large number, especially if we want to study the pattern of interaction in all 44 periods.

However, if we take advantage of our data being ordinal, we can reduce the number of parameters and, in addition, obtain parameters describing the direction of association. The two models that follow are both derived by restricting the parameter space in model II by linear restrictions on the parameters.

Model III, in which LC is treated as ordinal, describes the probability for the revision (R) to be made in the expectation variable conditional on whether the firm underestimated, correctly estimated or overestimated the past change in the variable to be predicted (LC).

$$(24) \qquad \begin{aligned} &MODEL\ III:\ \log(\pi_{rk}^{R,LC}) = \mu_{III} + u_r^{R} + u_k^{LC} + \beta_r^{LC}(v_k - \bar{v}), \\ &where\ \ v_k = k\ \ and\ \ \bar{v} = \frac{1}{3} * \sum_{k=1}^{k=3} v_k = 2 \end{aligned}$$

The linear restrictions in model III are derived by including the difference between the score on LC (k) and its average score; $(v_k-\bar{v})$[6]. The bivariate interaction between R and LC, is thereby restricted to be linear in LC with the slope β_r^{LC}. A positive value on β_r^{LC} increases the possibility for the event {r,k} to occur if the score on LC is above the average score (i.e. k=3), and reduces the possibility for the event if the score on LC is below its average (i.e. k=1). The probabilities are adjusted in the opposite direction if β_r^{LC} is negative. Under the null of no association, the slope parameters will all equal zero.

[6] If we let R be the row variable and LC the column variable in the cross-table, model III is known as the loglinear row effects model.

The distance between two rows ($R=r_1$ and $R=r_2$) is a linear function of the coloumn variable (LC), with slope (β_{r1}^{LC} - β_{r2}^{LC}), as shown in (25).

$$(25) \qquad MODEL\ III \Rightarrow \log(\pi_{r_1k}^{R,LC}) - \log(\pi_{r_2k}^{R,LC}) = (u_{r_1}^{R} - u_{r_2}^{R}) + (\beta_{r_1}^{LC} - \beta_{r_2}^{LC})(v_k - \bar{v})$$

If the distance (β_1^{LC} - β_3^{LC}) is negative, the possibilities for the event $\{r,k\} \in (\{1,1\}, \{3,3\})$ are increased compared to the case of no association, and the possibilities for the event $\{r,k\} \in (\{1,3\}, \{1,3\})$ are reduced. This is the case of positive association which is the assumed direction of association according to the error-learning model. In the case of negative association the distance (β_1^{LC} - β_3^{LC}) is positive. As a result, the hypothesis of no association can be tested for, against the alternative of positive/negative association, by use of an ordinary t-test on the distance β_1^{LC} - β_3^{LC} in model III. In addition seperate t-tests are run on β_1^{LC} and β_3^{LC}. In the case of positive association, β_1^{LC} is negative and β_3^{LC} is positive; increasing (decreasing) the probability for an upward (downward) revision when confronted with an underestimation (overestimation) last period.

In model IV, which is known as the linear-by-linear association model, we have taken advantage of both R and LC being ordinal.

$$(26) \qquad \begin{aligned} &MODEL\ IV: \quad \log(\pi_{rk}^{R,LC}) = \mu_{IV} + u_r^{R} + u_k^{LC} + \beta(v_k - \bar{v})(w_r - \bar{w}), \\ &where \quad v_k = k\ ,\quad w_r = r\ ,\quad \bar{v} = \frac{1}{3} * \sum_{k=1}^{k=3} v_k \quad and \quad \bar{w} = \frac{1}{3} * \sum_{r=1}^{r=3} w_r \end{aligned}$$

The linear restrictions in model IV are derived by including the difference between the score on the variables and their average score; (v_k-$\bar{v}$) and (w_r-$\bar{w}$). The departure from independence is linear in both R and LC with slope equal β, hence the name linear-by-linear association model. If β is positive, there is an increased probability for equally ordered observations of R and LC (the variables have scores on the same side of their average scores), while a negative β increases the probability for unequally ordered observations. Hence, positive association between the revision term (R) and the correction term (LC), which is the case under the error-learning model, should give a positive slope. We apply a t-test on β to test for no association against positive or negative association.

Model IV is the most restrictive one of the presented models, leading the number of freely estimated parameters describing the bivariate association to only one, while model III leads to two freely estimated parameters[7] describing the association (a third one is calculated using the restriction on the sum of the β_r's). All restrictions on the remaining parameters from model II, still hold. The linear restrictions necessary when we go from model II to model III or IV, can be tested for by use of a Likelihood ratio test[8] being based on the reduction in the log likelihood when going from model II to a more restrictive one.

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[7] Parameter restriction in model III in addition to usual ones in loglinear probability models:

$$\sum_{r=1}^{r=3} \beta_r^{LC} = 0$$

[8] The degrees of freedom are 2 when going from model II to model III and 3 when going from model II to model IV.

6 Results

Different tests have been conducted and statistics have been calculated in order to explore the formation of expectations concerning prices of firms' products in exports and domestic markets, and demand of firms' products in the same markets. Incoming orders are used as proxy for demand. According to the remarks made earlier in this paper, some of the statistics are given just for the purpose of describing the patterns of association. When formal tests are run, the null of no association is tested against the alternative hypothesis of some sort of an extrapolative mechanism, i.e. association.

In table III and IV the distributions of EY by LPY and EY by LEY, calculated over all periods, are shown. The association between the expected change (EY) and the last observed change (LPY) is assumed to be positive in the following three models; the general extrapolative model restricted to include only the first lag, the model of static expectations and the model of adaptive expectations. We also assume the association between the current (EY) and past (LEY) expectation to be positive in the adaptive model. A strong association between EY and LEY indicates that the underlying general extrapolative mechanism has a long memory.

Table III: EY by LPY. Observed frequencies. Percent.

		LPY up	LPY no change	LPY down	Sum
Domestic prices					
	up	10.7	15.5	0.5	26.7
EY	no change	15.8	49.0	3.4	68.2
	down	0.4	1.9	2.8	5.1
	Sum	26.9	66.4	6.7	100
Export prices					
	up	10.6	13.9	0.8	25.3
EY	no change	14.1	46.9	5.3	66.3
	down	0.6	2.8	5.1	8.5
	Sum	25.3	63.6	11.2	100.1
Domestic demand					
	up	6.8	6.8	8.1	21.7
EY	no change	11.2	36.7	10.2	58.1
	down	7.6	5.2	7.5	20.3
	Sum	25.6	48.7	25.8	100.1
Export demand					
	up	7.1	6.6	6.0	19.7
EY	no change	11.2	36.8	11.9	59.9
	down	4.8	4.8	10.7	20.3
	Sum	23.1	48.2	28.6	99.9

Table IV: EY by LEY. Observed frequencies. Percent.					
Domestic prices		LEY			Sum
		up	no change	down	
	up	10.1	15.7	0.5	26.3
EY	no change	16.1	49.7	2.8	68.6
	down	0.6	2.8	1.7	5.1
	Sum	26.8	68.2	5.0	100
Export prices					
	up	10.2	13.8	0.9	24.9
EY	no change	14.5	48.0	4.1	66.6
	down	1.0	4.0	3.5	8.5
	Sum	25.7	65.8	8.5	100
Domestic demand					
	up	7.0	8.9	5.1	21.0
EY	no change	9.1	40.8	8.5	58.4
	down	5.3	8.5	6.8	20.6
	Sum	21.4	58.2	20.4	100
Export demand					
	up	7.2	9.0	3.3	19.5
EY	no change	9.6	41.4	9.1	60.1
	down	3.2	9.2	8.1	20.5
	Sum	20.0	59.6	20.5	100.1

We find in table III that, independent of whether firms respond that they most recently have observed an increase, a decrease or no change, quite a lot of them expect the variables to remain unchanged during the coming period (quarter). This tendency is found for both prices and demand variables, but the concentration of expectations in the category "no change" is somewhat higher for prices. Most of those expecting prices to change, expect prices to move in the same direction as observed between the two previous periods. This tendency is also found, but far from being strong, for the expectations of domestic demand. With regard to expectations of foreign demand, those firms expecting demand to change are equally divided on expecting it to increase or decrease independent of what they most recently have observed. For all four variables, the observations are more concentrated along the diagonale than predicted by the null hypothesis of no association[9].

[9] Predicted cell frequencies under the hypothesis of no association equal $\hat{n}_{ij} = n_{i.}\, n_{.j}/n_{..}$, where i denotes the row variable and j the column variable.

The same pattern of association as between EY and LPY can be found between EY and LEY in table IV, but with a more clear positive association also for the demand variables. The deviation from the null of no association is however weaker for the association between EY and LEY than between EY and LPY.

According to the two tables, we may make a first, tentative conclusion: The observed frequencies for the price variables are more in accordance with a extrapolative or adaptive expectation mechanism than are the frequencies for the demand variables. But, the high concentration in the "no change" category independent of the last observed or expected direction of change may indicate some sort of regressive expectations. The high concentration in the "no change" category may also be due to measurements errors. More detailed results will be given in the following pages, which may strenghten or weaken this first impression.

6.1 The General Extrapolative Model

As already mentioned, the data does not allow us to include more than one lag of former observations of the variable to be predicted at the time when we test the general extrapolative model. Instead tests of the association between the expectation and lagged observations for the first, second, third and fourth lag have been conducted separately in two-dimensional tables. This approach prevents us, unfortunately, from controlling for the influence of other lags than the one included at the moment.

The results are presented in figures 1-8 (appendix 1). Two different test-statistics are applied; the LR-statistics and the Goodman and Kruskal's gamma (GKG), the first testing for nominal association the second for ordinal association. If association is present, we would expect the association to be positive. The LR-values are shown in figures 1-4, while figures 5-8 show the t-values associated with the gamma statistics. The null hypothesis of no association should be rejected if the observed LR-value or the t-values are above their critical levels. The critical levels associated with a significance probability of 1 percent and 5 percent are marked in the figures.

When we test for association between EY and LPY (1.lag), what we test are in fact the model of static expectations. The association between EY and L^4PY may reveal seasonal factors in the formation of expectations because the fourth lag relates to the same quarter as EY, but one year earlier.

The results suggest that some sort of extrapolative mechanism is at work when firms predict the price movements. For both price variables the null of no association between expectations and firms' latest observations of the variable to be predicted, is rejected in all periods. In most periods the association is positive. The number of periods in which the null is rejected, is somewhat decreasing when the period of time between the observation and the expectations decrease. This may be taken as an indication of less weight put on earlier observations. The emphasize put on the fourth lag are about the same (or even bigger) than the emphasize on the third lag and may be due to seasonal factors. For the association between EY and L^jPY, both tests indicate the association to weaken over the estimation period. This tendency is strongest for the association between EY and LPY and may be due to firms gradually being less extrapolative in their formation of expectations.

The results for expectations of demand for own products are less impressing. The LR-statistics for expectations of export demand give a picture similar to that found for the price variables, but the GKG-statistics are not significant different from zero in about half of the periods, especially in the last part of the period studied. Although the LR-statistics for domestic demand indicate association to be present, the association is more often negative than positive according to the GKG-statistics. The results for domestic demand do also differ from those found for the other variables, in that we often find a positive association between EY and L^4PY (in about 25% of the periods). This may be due to a strong sesonal component in the formation of expectations of domestic demand. The findings may indicate a regressive expectations mechanism for domestic demand. The reader should also be aware of the fact that we are analyzing variables related to the rate of change, while the firms may however, posess extrapolative expectations conserning the level of demand. Extrapolative expectations of the level of demand will give raise to a negative association between the expected change and the observed change between period t and t-1[10].

6.2 Adaptive Expectations

Descriptive measures have been calculated in order to investigate whether the observed expectations can be described according to the model of adaptive expectations (see (4) and (13)). But, as already mentioned, the results can not be used to draw any statistical conclusions. Two types of measures will be presented; the first being the LR-statistics between EY and LEY and between EY and LPY. In the case of adaptive expectations association will be present and the observed LR-statistics should differ from zero. In addition to the LR-statistics, a set of parameters (the λ's defined in (21)) which are derived from the bivariate interaction parameters in the loglinear probability model (see (19)), have been calculated. These should all be positive in the case of adaptive expectations.

The LR-statistics are presented in figures 9-12 (appendix 1). Each figures contain the statistics for the association between both pair of variables; EY and LEY, and EY and LPY. The 1-percent significance level in the $\chi^2(4)$-distribution is marked by the horizontal line in the figures, indicating at which level the null-hypothesis of no association would have been rejected if significance tests could have been conducted to the data. The observed LR-statistics for the association between the expected direction of change (EY) and the most recently observed direction of change (LPY) lie above the LR-statistics for the association between the expected direction of change (EY) and the previous made expectation (LEY) for domestic (fig.9) and export prices (fig.10) and for domestic demand (fig.11). The distance between the two statistics is greatest in the first part of the observation period. In later periods the statistics describing the degree of association between the expectations and the most recently observed change, declines. One tentative conclusion may be that firms, during the seventies, had a short memory, in that expectations about the variables' future direction of change were more influenced by the most recently observed direction of change than by the previous held expectations. This is in accordance with the results for the general extrapolative model. From then on, the influence on expectations from both variables (lagged observations and lagged expectations) declined. Expectations of demand in export markets (fig.12), seem to be equally influenced by both the most recently observed change, and by the previous held expectations.

The next figures (13-20) in the apendix show the estimated values of the λ's. Under the hypothesis of adaptive expectations these should be positive. Positive values of $\lambda_{pp'q}$ and $\lambda_{pp'm}$ (q,m=p) can be interpreted as a higher possibility for firms expecting (EY) the same direction of change from time t to t+1, as expected (LEY) or observed (LPY) from period t-1 to t, than for expecting something else. The loglinear probability model could not be estimated for all periods and especially for the price variables this was a problem. Only results from periods in which all bivariate interaction parameters could be estimated are reported.

The results for the expectations of prices in domestic markets as shown in figure 13a-c and 14a-c, do not support the hypothesis of adaptive expectations. Despite some rather high, positive values, most of the estimated λ's are positive but small, or negative. This is true for the bivariate interaction between both pair of variables (EY*LPY and EY*LEY). Look at the values for λ_{212}

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[10] Extrapolative expectations for the level variables and consequences for the expctations of the rate of change:

$$Y_t^e = \gamma + \delta_1 Y_{t-1} + \delta_2 Y_{t-2} \quad \Rightarrow \quad y_t^e = (\gamma + (\delta_1 + \delta_2 - 1) Y_{t-3}) + (\delta_1 - 1) y_{t-1} + (\delta_1 + \delta_2 - 1) y_{t-2}$$

(fig.13b and 14b) as an example. This parameter is negative in several periods for both sets of association. A negative value on this indicates that the bivariate interaction between EY and LPY (or EY and LEY) leads to a higher possibility for firms to expect the prices to increase than to remain unchanged if they recently have observed unchanged prices (or expected prices to remain unchanged between the previous periods). In the case of adaptive expectations we would have expected the possibility for firms' to expect the prices to remain unchanged to be higher than for them expecting the prices to increase in the above described situation.

The estimated λ's for the expected direction of change for prices in export markets, are given in figures 15a-c and 16a-c. Most of the parameters have been estimated to be positive, but for the bivariate interaction between EY and LPY, we find several small positive or negative values for λ_{121} , λ_{212} and λ_{232} (fig.15a-b). Three of the parameters for the bivariate interaction between EY and LEY are often estimated to be quite small; λ_{121} , λ_{212} and λ_{232} (fig.16a-b).

The results for firms' expectations of domestic demand (fig.17a-c and 18a-c), do not support the hypothesis of adaptive expectations. Especially λ_{121} , λ_{131} (fig.17a) and λ_{313} (fig.17c) derived from the bivariate interaction parameters for EY*LPY show several cases of small positive or negative values. The parameters derived from the bivariate interaction between EY and LEY (fig.18a-c), are most often positive, but rather close to zero.

Also for the bivariate interaction between EY and LPY (fig.19a-c) for expectations of demand in export markets, some of the parameters have several periods with small positive or negative values (λ_{121} , λ_{131} and λ_{313}). The estimates of the parameters derived from the estimated bivariate interaction between EY and LEY (fig.20a-c) are positive, but often quite small.

The results presented can not, as stressed several times, be used to confront our data with any statistical tests of the hypothesis of adaptive expectations. But used to describe the pattern of association found in the data, the different measures presented do not give any overwhelming support to the hypothesis. This results indicate though that the adaptive model is too restrictive, or that our data do not contain enough information.

6.3 The Error-Learning Model

In the error-learning model ((6) and (13)) the revised expectations (the difference between the expectations made at time t-1 and t concerning the variable at time t and t+1) depend on the correction made last period (the difference between the realized and expected value of the variable at time t-1). The association between the revised expectations (R) and the correction made last periode (LC) should be positive if expectations are formed according to the error-learning model. We have considered three different loglinear probability models describing the patterns of association during estimation. The results are given in tables V - VIII. The upper part of the tables tells which variables that have been treated as nominal or ordinal in the different models. The first two rows with figures give the results from the Likelihood ratio tests of the restrictions imposed on the bivariate interaction parameters while going from model II to model III or IV. The next three rows give the results from the Likelihood ratio tests of the hypothesis of no association within the framework of the three different models. While the LR test is a test of nominal association, the bottom part of the tables give the results from different tests of ordinal association against the alternative of positive association. The GKG-statistics is applied when there is no restrictions on the pattern of association (model II). In model III and IV we apply t-tests to the estimated parameters.

The first model is the less restrictive and the null of no association is rejected in all periods (44) for all four variables against the alternative of association. The GKG has been calculated and the results indicate the association to be positive in all periods for both price variables and demand in export markets, while no significant direction of association is found for domestic demand. This is in accordance with the results from the general extrapolative model.

Looking at the price variables, the results show that the restrictions imposed on the bivariate interaction when we go from model II to model III or IV are rejected in about 1/2 of the periods. But according to model III and IV, the hypothesis of no association is rejected against the alternative of positive association, in all periods in which the data fits the different models. So, for the two price variables, we can conclude that our data supports the error-learning model.

The restrictions imposed by the more restrictive models (III and IV) are quite often rejected for the demand variables. When not rejected, the results are in favour of the error-learning model.

Table V: Domestic prices

		Model II	Model III	Model IV
Nominal variables		R, LC	R	
Ordinal variables			LC	R, LC
Periods of not rejecting the model	$X^2(2)$		22	
	$X^2(3)$			19
Periods of rejecting; H^0: no association vs H^1 : association	$X^2(4)$	44		
	$X^2(2)$		22	
	$X^2(1)$			19
Periods of rejecting H^0: parameter = 0 vs.:	GKG> 0	44		
	$\beta_1 < 0$		22	
	$\beta_3 > 0$		22	
	$\beta_1 - \beta_3 < 0$		22	
	$\beta > 0$			19

Table VI: Export prices				
		Model II	Model III	Model IV
Nominal variables		R, LC	R	
Ordinal variables			LC	R, LC
Periods of not rejecting the model	$X^2(2)$		29	
	$X^2(3)$			24
Periods of rejecting; H^0: no association vs H^1 : association	$X^2(4)$	44		
	$X^2(2)$		29	
	$X^2(1)$			24
Periods of rejecting H^0: parameter = 0 vs.:	GKG > 0	44		
	$\beta_1 < 0$		29	
	$\beta_3 > 0$		29	
	$\beta_1 - \beta_3 < 0$		29	
	$\beta > 0$			24

Table VII: Domestic demand				
		Model II	Model III	Model IV
Nominal variables		R, LC	R	
Ordinal variables			LC	R, LC
Periods of not rejecting the model	$X^2(2)$		6	
	$X^2(3)$			9
Periods of rejecting; H^0: no association vs H^1 : association	$X^2(4)$	44		
	$X^2(2)$		6	
	$X^2(1)$			9
Periods of rejecting H^0: parameter = 0 vs.:	GKG > 0	6		
	$\beta_1 < 0$		6	
	$\beta_3 > 0$		6	
	$\beta_1 - \beta_3 < 0$		6	
	$\beta > 0$			9

Table VIII: Demand in export markets				
		Model II	Model III	Model IV
Nominal variables		R, LC	R	
Ordinal variables			LC	R, LC
Periods of not rejecting the model	$X^2(2)$		8	
	$X^2(3)$			10
Periods of rejecting; H^0: no association vs H^1 : association	$X^2(4)$	44		
	$X^2(2)$		8	
	$X^2(1)$			10
Periods of rejecting H^0: parameter = 0 vs.:	GKG > 0	44		
	$\delta_1 < 0$		8	
	$\beta_3 > 0$		8	
	$\delta_1 - \beta_3 < 0$		8	
	$\beta > 0$			10

6.4 Conclusion

Especially for the two price variables, but also for the demand in export markets, our data give evidence of firms' expectations being formed in accordance with the general extrapolative model. The strongest weight is placed on the most recent observation of the direction of change, indicating a short memory. The weights seem to be declining, but with some more weight put on the fourth lag indicating a seasonal pattern. For the demand on domestic markets, none of our models fit the data. But as already mentioned, a regressive process may lie behind the observed expectations or the expected level of demand may have been formed according to the extrapolative model.

The adaptive model seem to be too restrictive in describing the data. This may be due to the restrictions given by the data being categorical and the sample being too small relative to how the observations are distributed.

It may seem somewhat peculiar that as far as the price variables and the demand in export markets are concerned, the data give stronger support to the error-learning than the adaptive model, as long as the former are a more restrictive model than the latter. The data do however, allow us to run more formal tests of the error-learning model than what have been possible for the adaptive one. The support to the error-learning model may also be due to spurious correlation which arises from both the revision term (R) and the lagged correction term (LC) being functions of previous held expectations (LEY).

Appendix 1

Figure 1. Domestic prices. EY and LjPY. Likelihood ratio statistics.

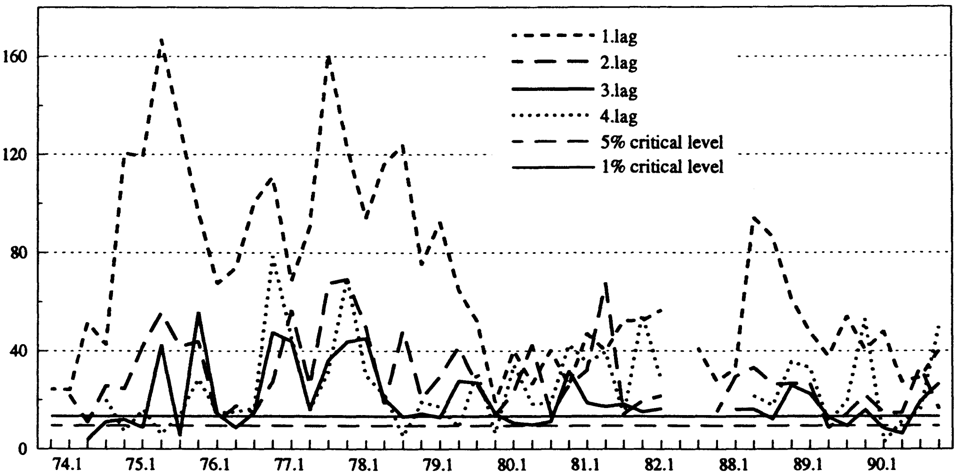


Figure 2. Export prices. EY and LjPY. Likelihood ratio statistics.

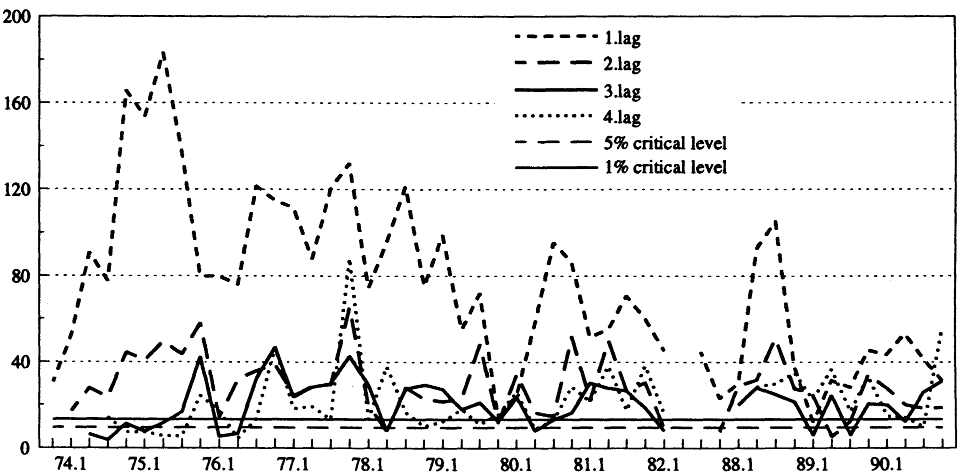


Figure 3. Domestic demand. EY and LjPY. Likelihood ratio statistics.

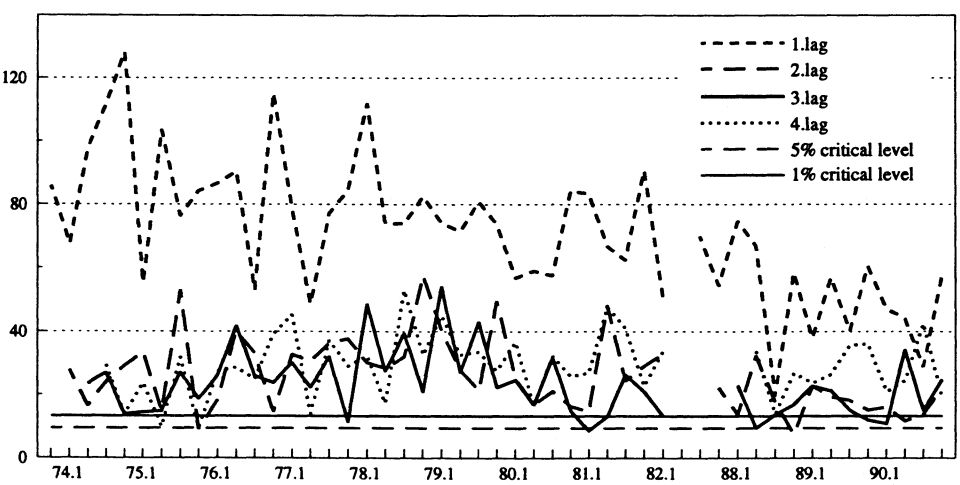


Figure 4. Export demand. EY and LjPY. Likelihood ratio statistics.

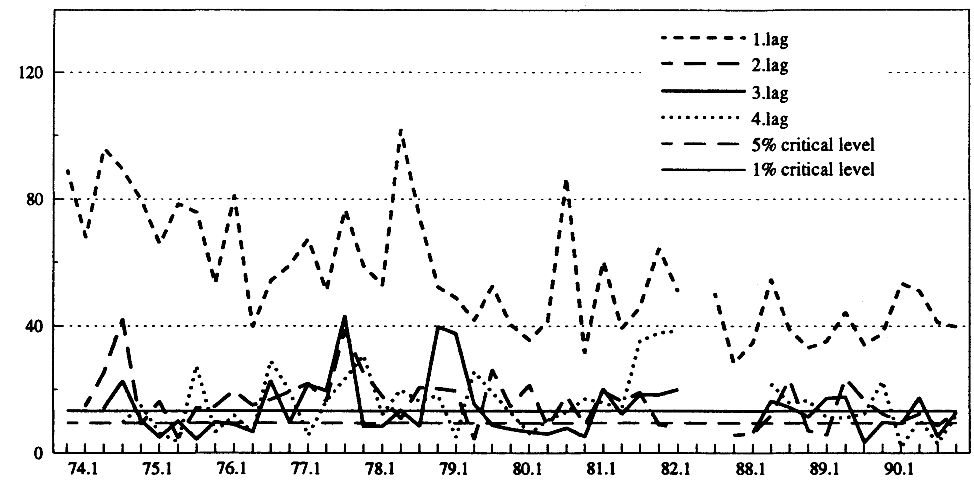


Figure 5. Domestic prices. EY and LjPY. Gamma test (t-values).

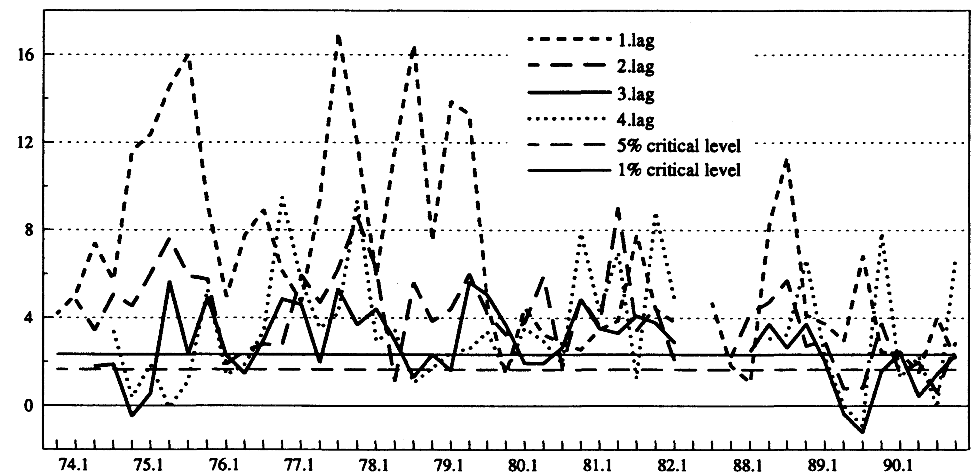


Figure 6. Export prices. EY and LjPY. Gamma test (t-values).

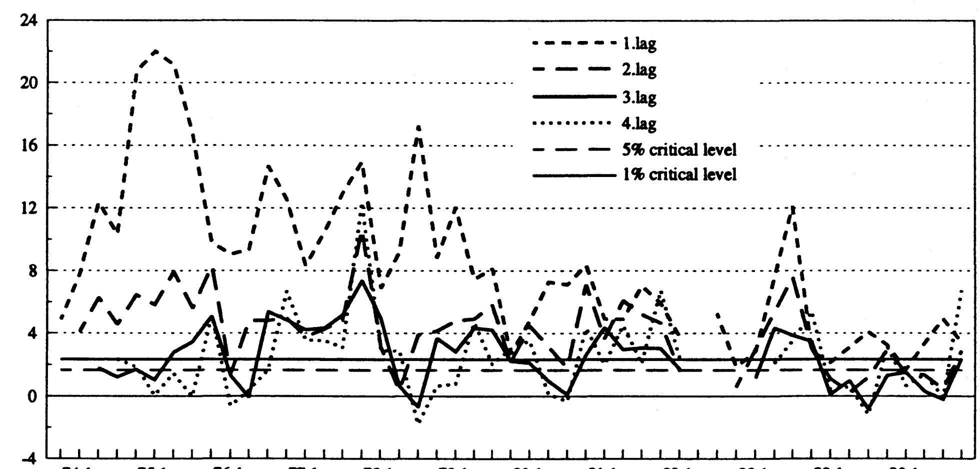


Figure 7. Domestic demand. EY and LjPY. Gamma test (t-values).

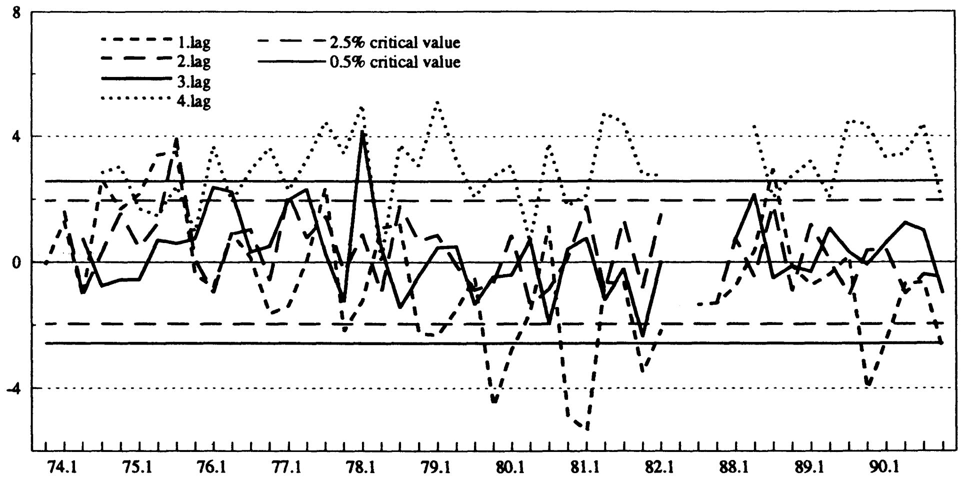


Figure 8. Export demand. EY and LjPY. Gamma test (t-values).

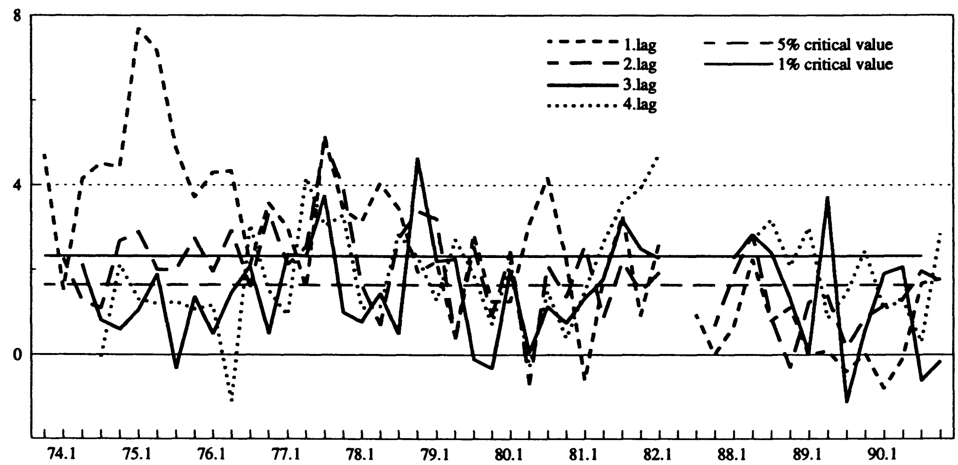


Figure 9. Adaptive expectations: Domestic prices. Likelihood ratio statistics.

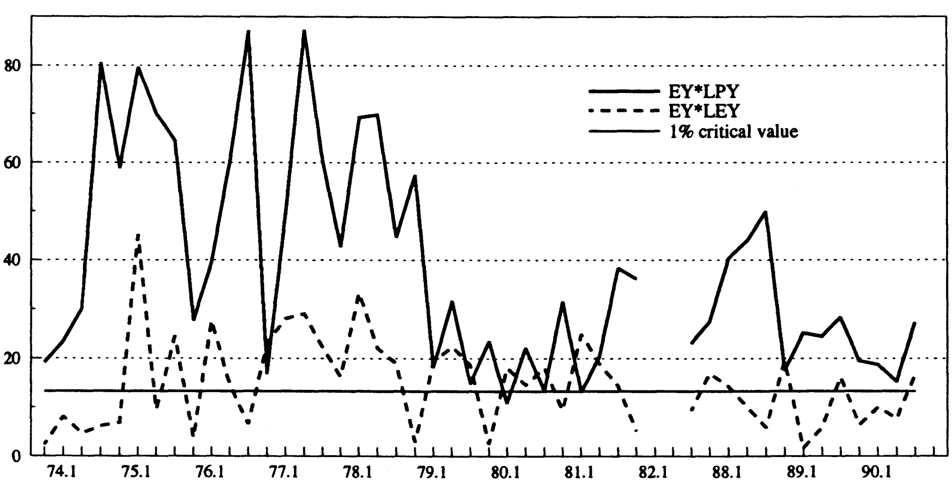


Figure 10. Adaptive expectations: Export prices. Likelihood ratio statistics.

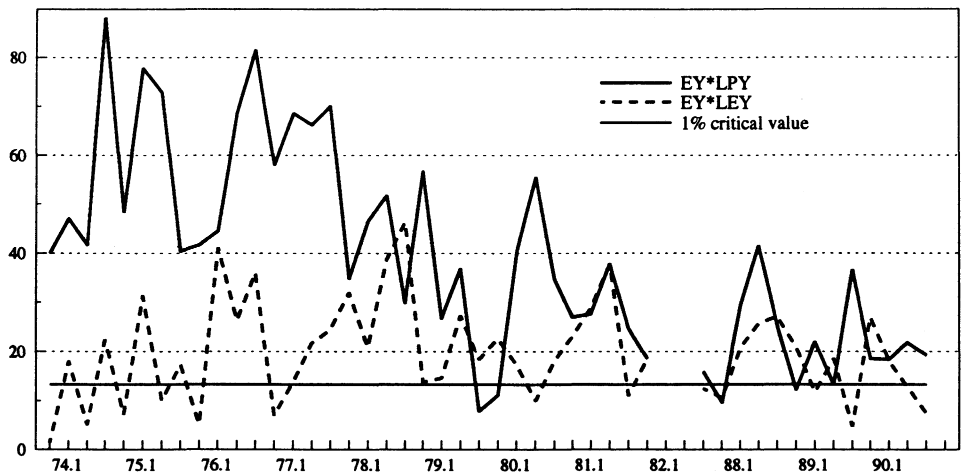


Figure 11. Adaptive expectations: Domestic orders. Likelihood ratio statistics.

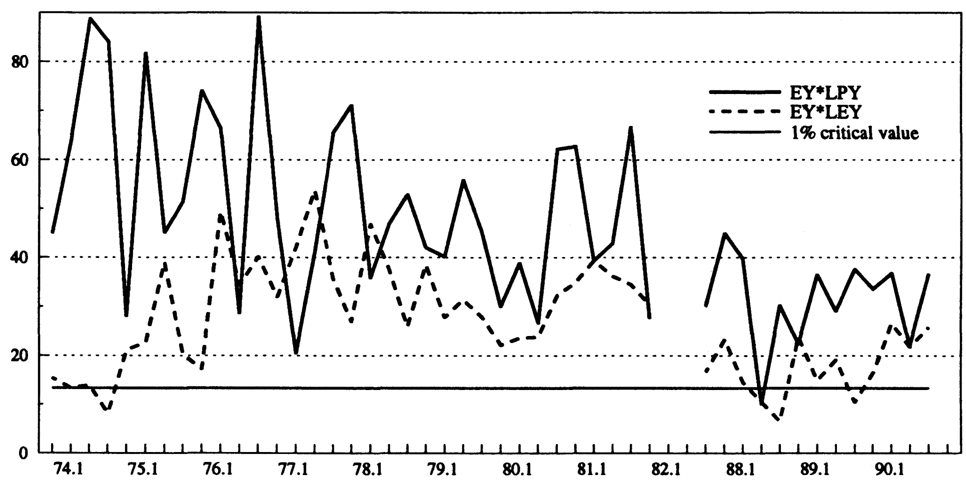


Figure 12. Adaptive expectations: Export orders. Likelihood ratio statistics.

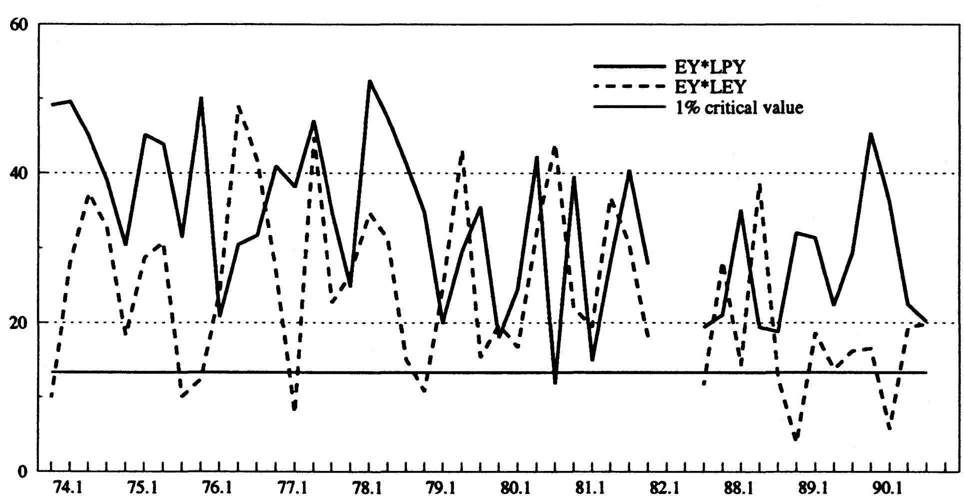


Figure 13a. Adaptive expectations: Domestic prices. EY*LPY: Lambda 121 and lambda 131.

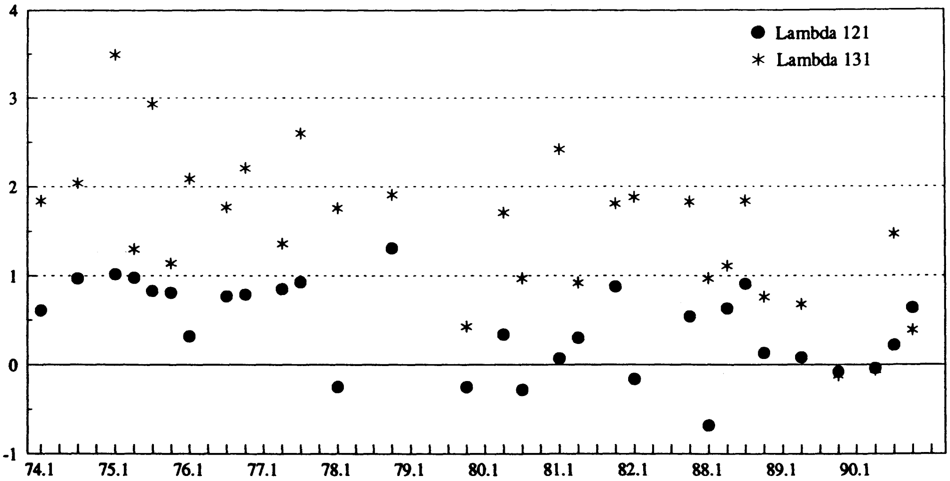


Figure 13b. Adaptive expectations: Domestic prices. EY*LPY: Lambda 212 and lambda 232.

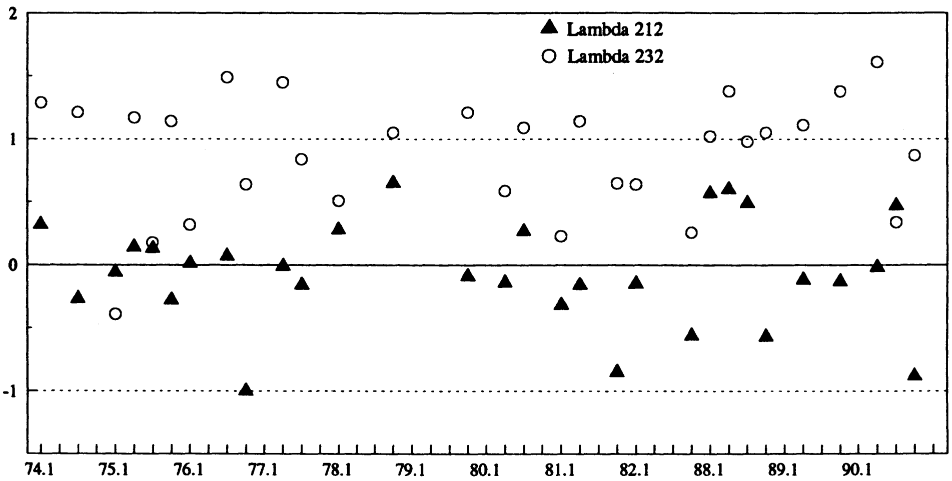


Figure 13c. Adaptive expectations: Domestic prices. EY*LPY: Lambda 313 and lambda 323.

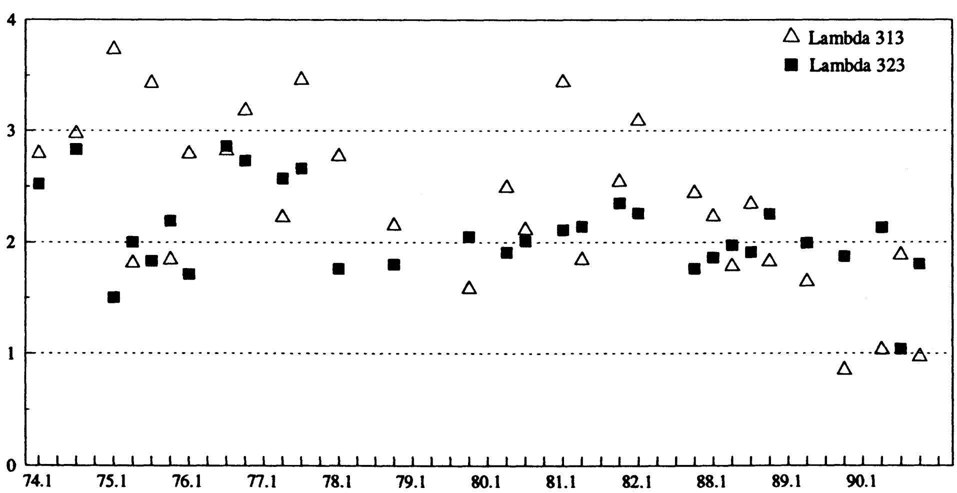


Figure 14a. Adaptive expectations: Domestic prices. EY*LEY: Lambda 121 and lambda 131.

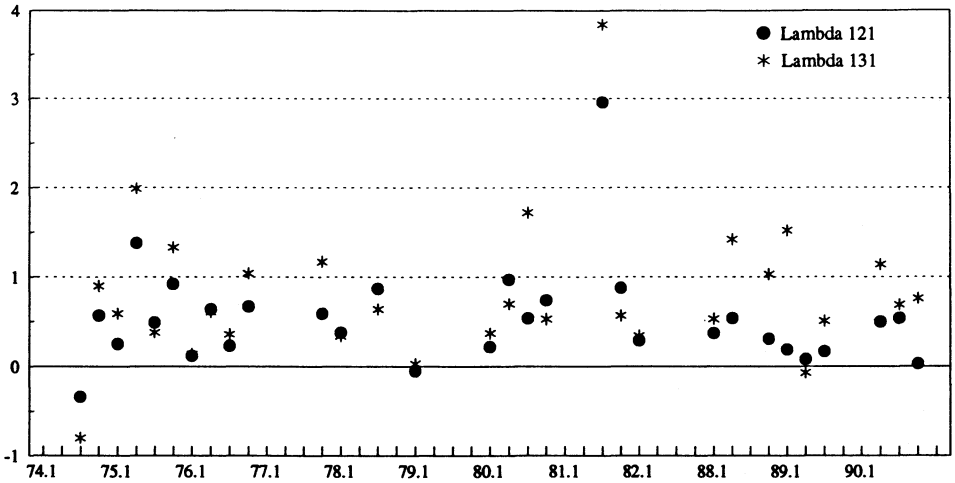


Figure 14b. Adaptive expectations: Domestic prices. EY*LEY: Lambda 212 and lambda 232.

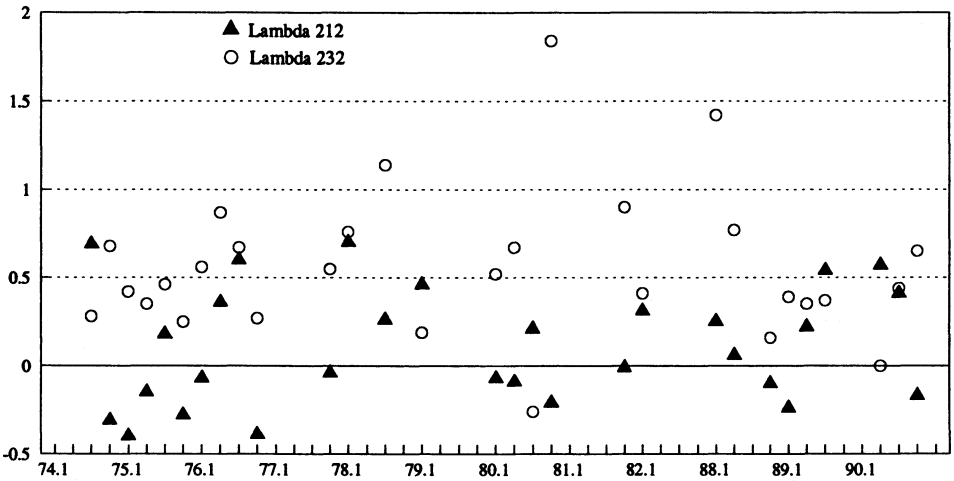


Figure 14c. Adaptive expectations: Domestic prices. EY*LEY: Lambda 313 and lambda 323.

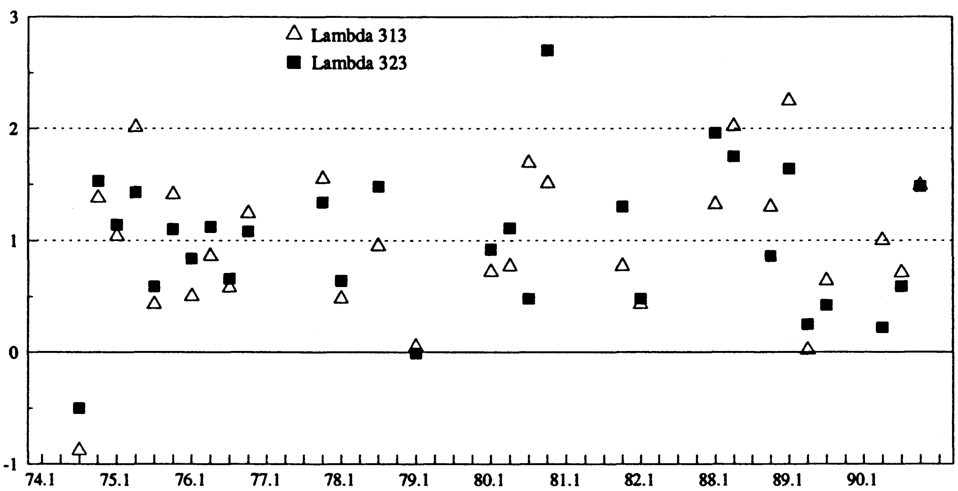


Figure 15a. Adaptive expectations: Export prices. EY*LPY: Lambda 121 and lambda 131.

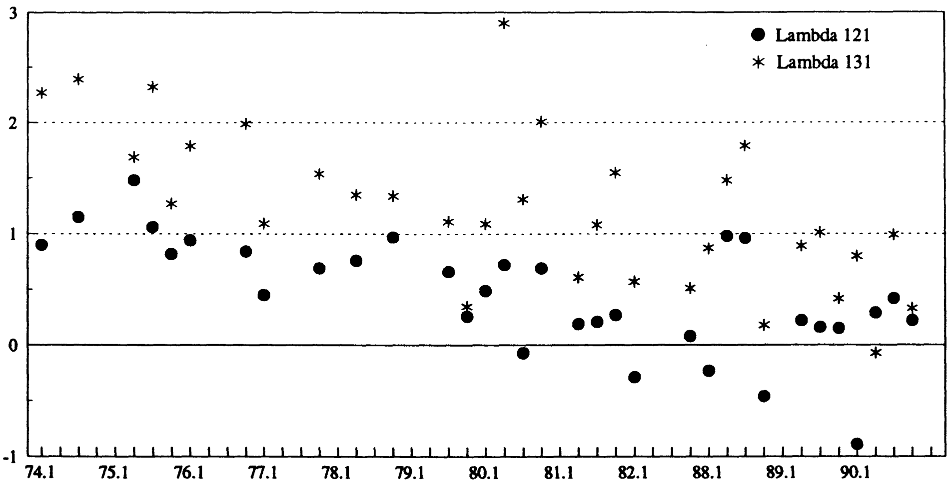


Figure 15b. Adaptive expectations: Export prices. EY*LPY: Lambda 212 and lambda 232.

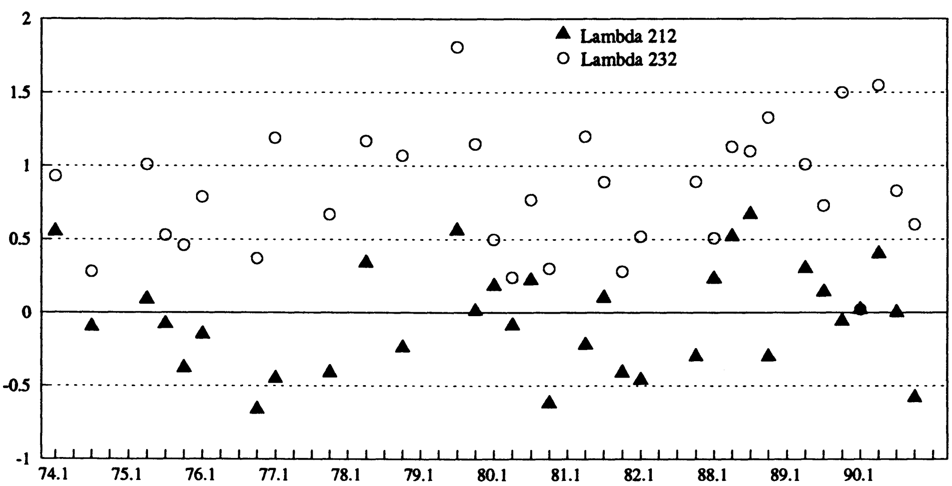


Figure 15c. Adaptive expectations: Export prices. EY*LPY: Lambda 313 and lambda 323.

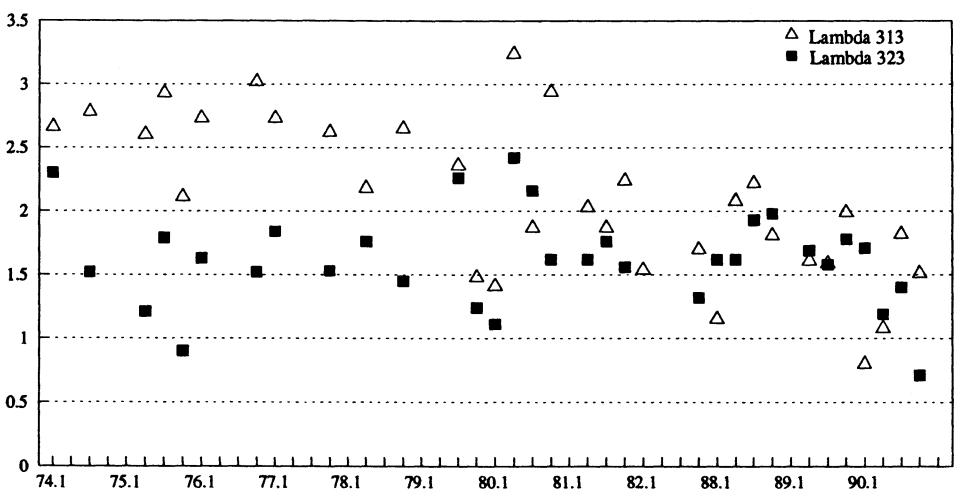


Figure 16a. Adaptive expectations: Export prices. EY*LEY: Lambda 121 and lambda 131.

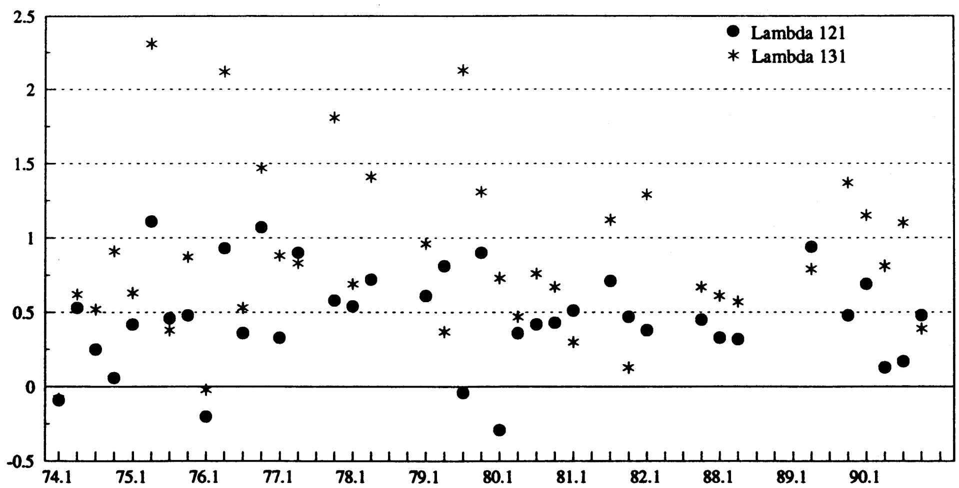


Figure 16b. Adaptive expectations: Export prices. EY*LEY: Lambda 212 and lambda 232.

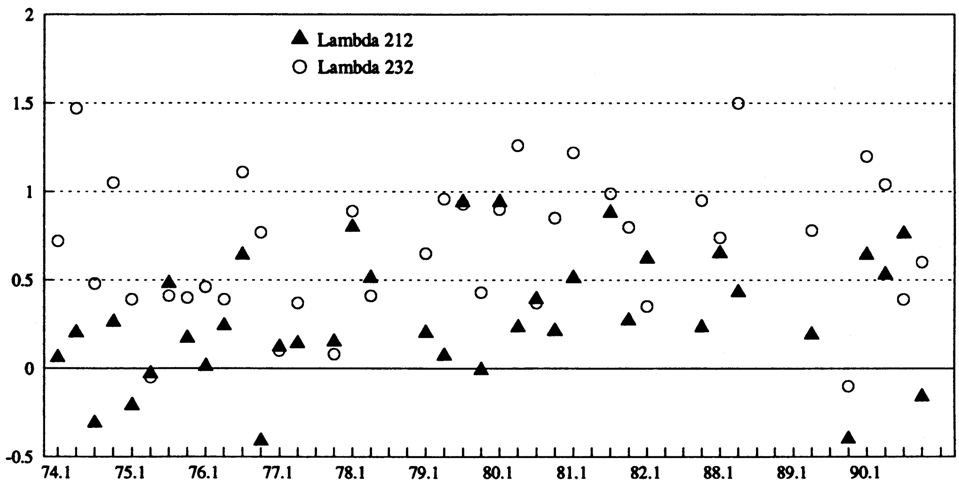


Figure 16c. Adaptive expectations: Export prices. EY*LEY: Lambda 313 and lambda 323.

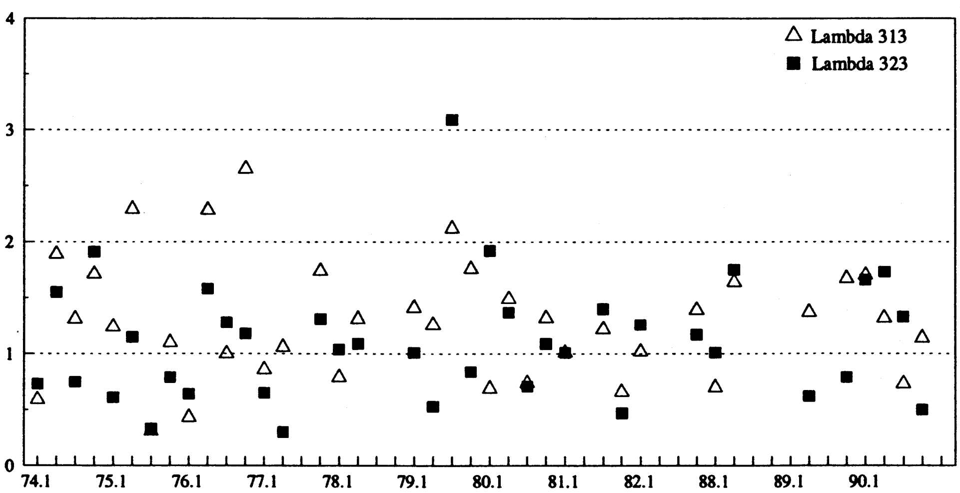


Figure 17a. Adaptive expectations: Domestic orders. EY*LPY: Lambda 121 and lambda 131.

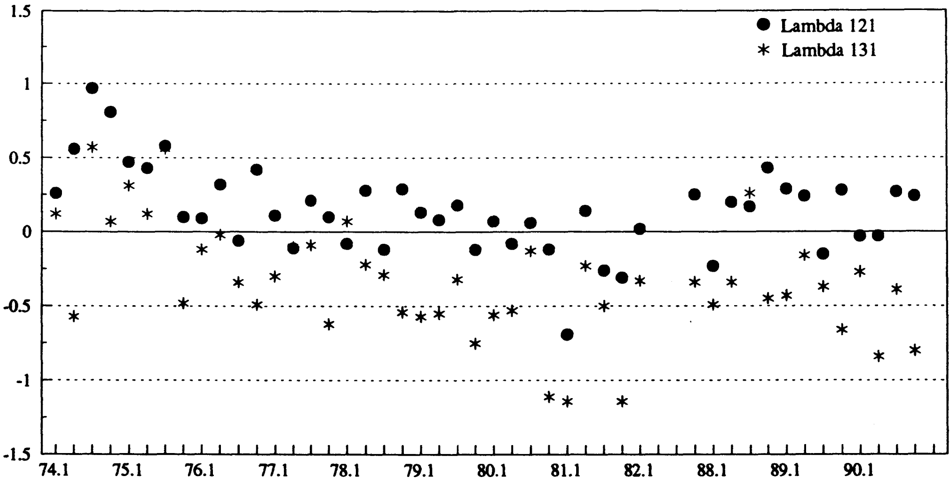


Figure 17b. Adaptive expectations: Domestic orders. EY*LPY: Lambda 212 and lambda 232.

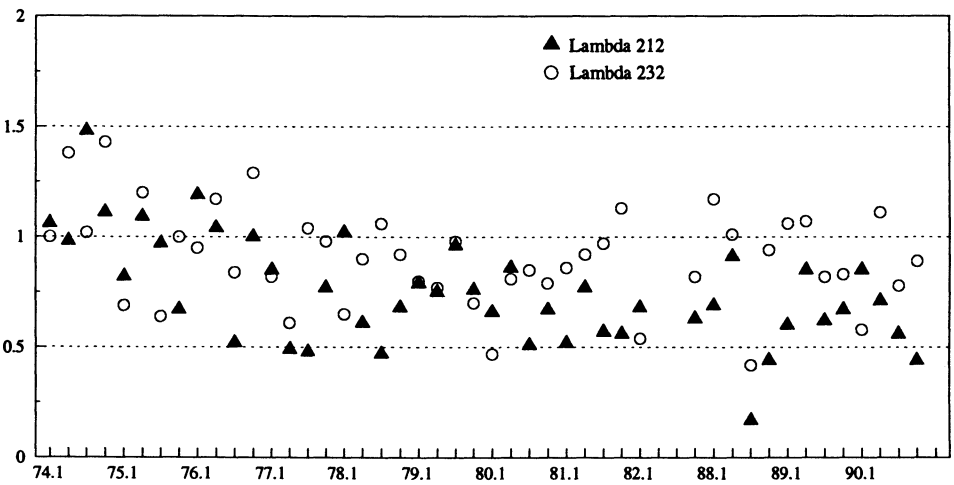


Figure 17c. Adaptive expectations: Domestic orders. EY*LPY: Lambda 313 and lambda 323.

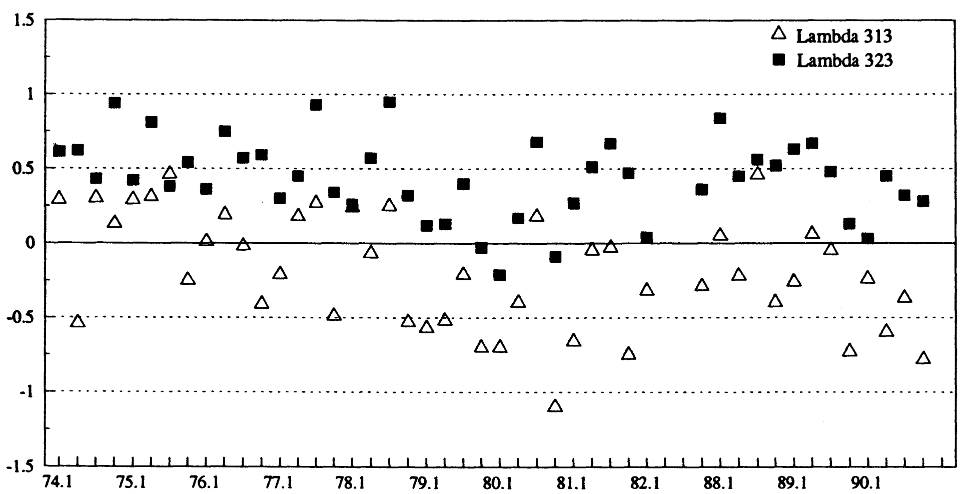


Figure 18a. Adaptive expectations: Domestic orders. EY*LEY: Lambda 121 and lambda 131.

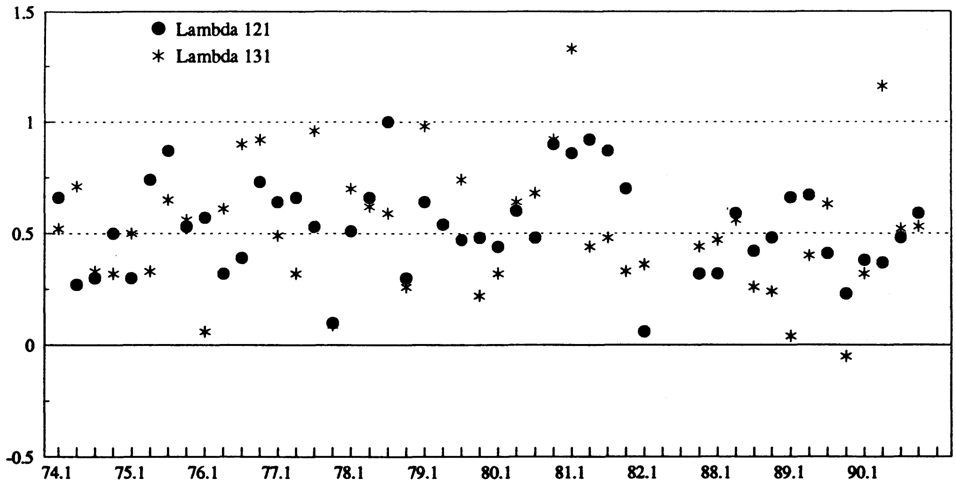


Figure 18b. Adaptive expectations: Domestic orders. EY*LEY: Lambda 212 and lambda 232.

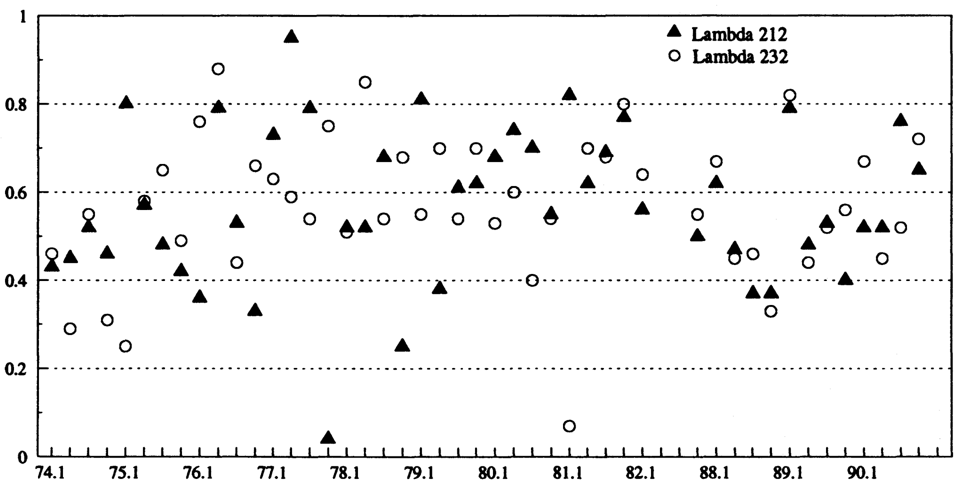


Figure 18c. Adaptive expectations: Domestic orders. EY*LEY: Lambda 313 and lambda 323.

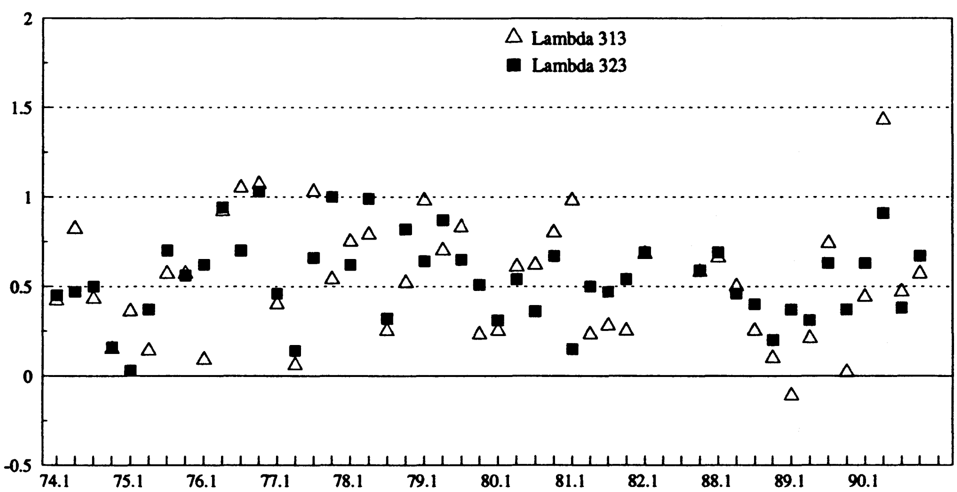


Figure 19a. Adaptive expectations: Export orders. EY*LPY: Lambda 121 and lambda 131.

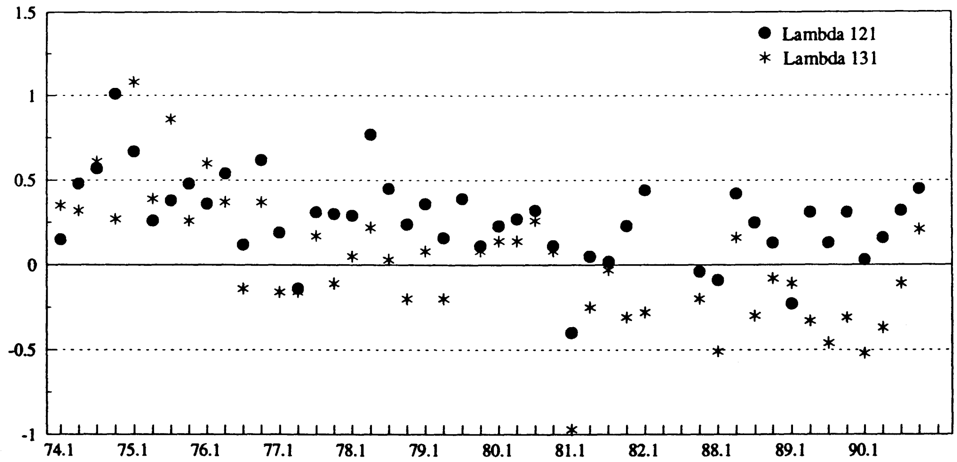


Figure 19b. Adaptive expectations: Export orders. EY*LPY: Lambda 212 and lambda 232.

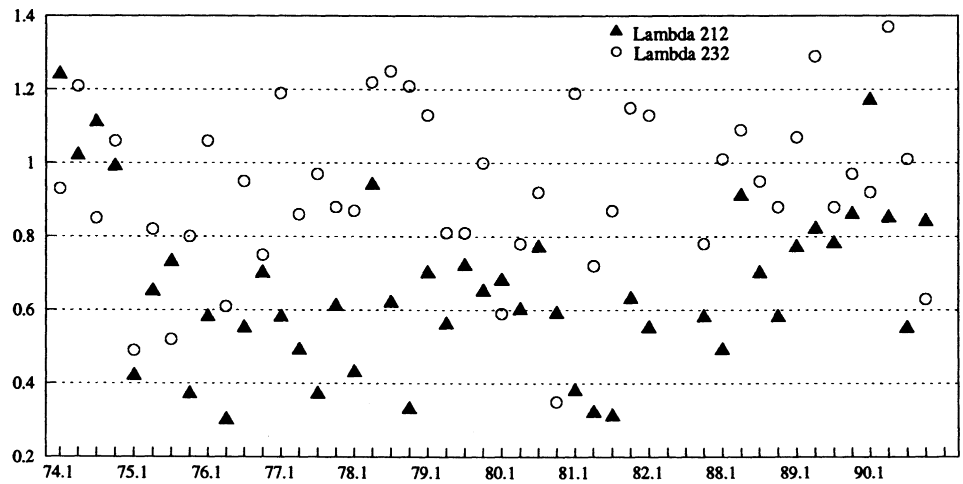


Figure 19c. Adaptive expectations: Export orders. EY*LPY: Lambda 313 and lambda 323.

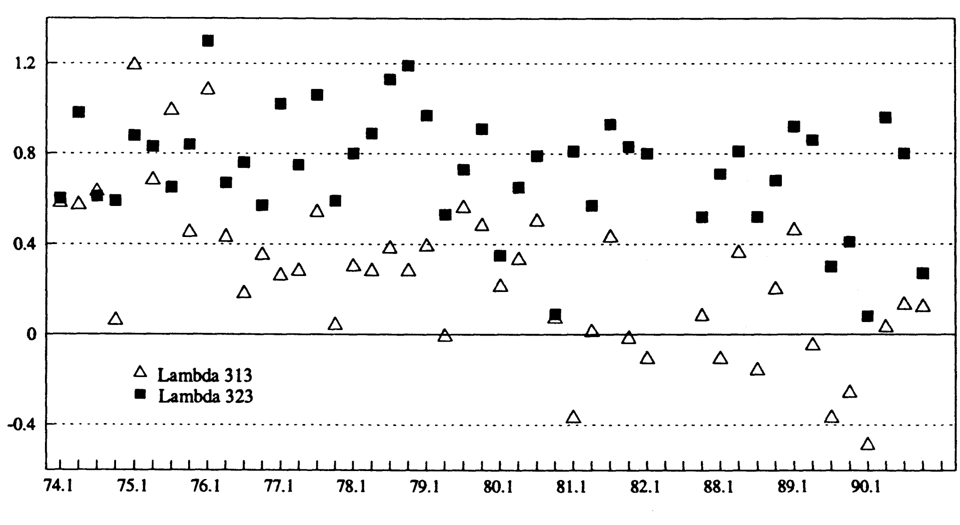


Figure 20a. Adaptive expectations: Export orders. EY*LEY: Lambda 121 and lambda 131.

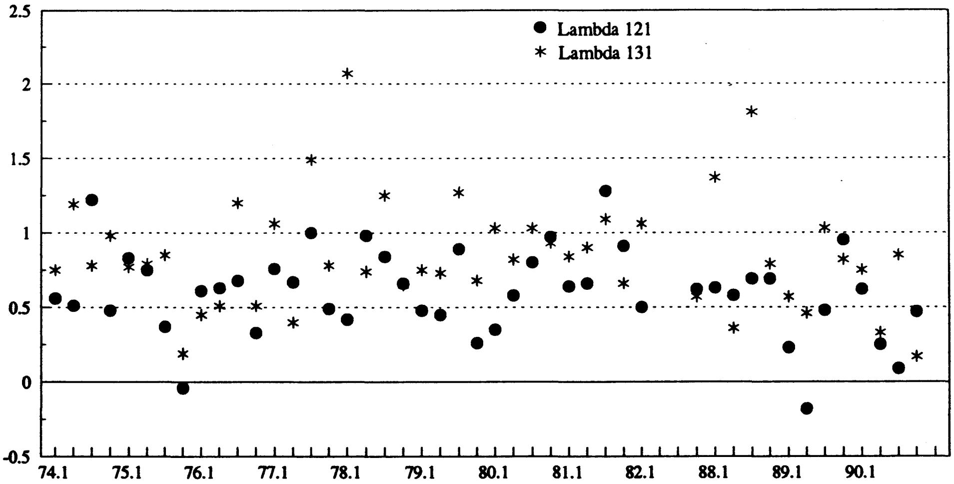


Figure 20b. Adaptive expectations: Export orders. EY*LEY: Lambda 212 and lambda 232.

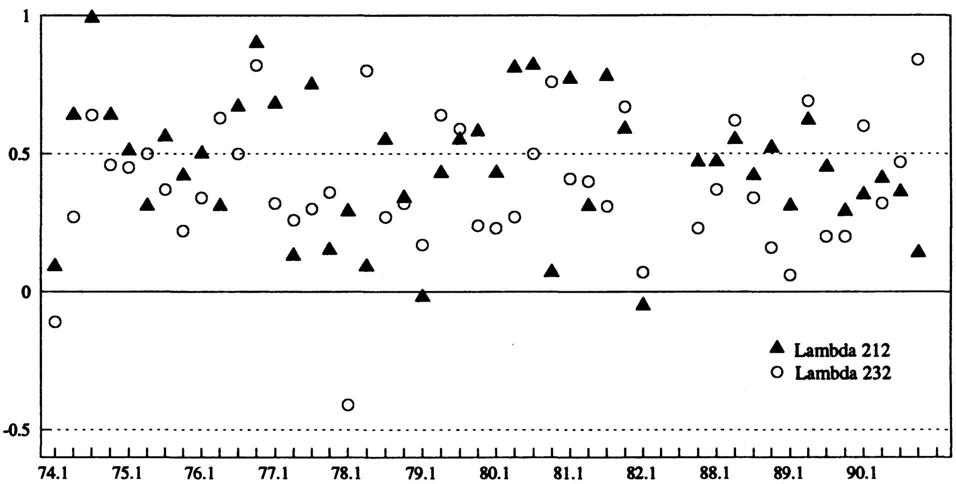
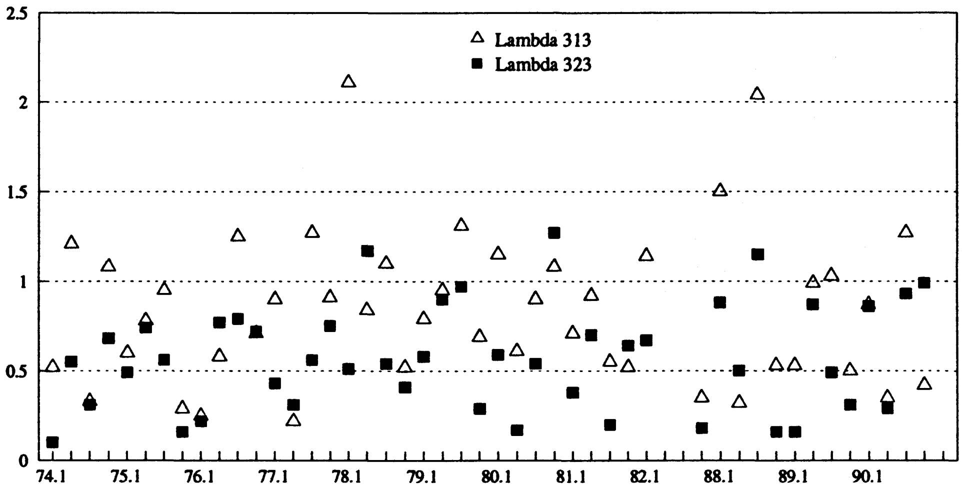


Figure 20c. Adaptive expectations: Export orders. EY*LEY: Lambda 313 and lambda 323.



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