INVESTMENT EXPECTATIONS OF ENTREPRENEURS

An empirical analysis at the firm level

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August 1996

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Abstract

This paper analyses entrepreneurial investment expectations at the firm level to determine whether or not the expectations for the current period are systematically biased. The empirical findings reveal that the expectations on investments are clearly biased and therefore we conclude that entrepreneurs do not show that they behave rationally. Outliers, identified via two different approaches, appear to play an important role in our estimation results but do not influence the overall conclusion that the investment predictions of entrepreneurs are biased.

Acknowledgments

The authors wish to thank Jos van Ommeren and two anonymous referees for helpful comments.

1. Introduction.

Understanding the way entrepreneurs form their expectations will offer better insight into the dynamics of a firm and, at a more aggregate level, into the economic development in a sector, region or economy (see also Van den Ende and Nijkamp, 1995). In this paper we will analyze entrepreneurial investment expectations at a micro-level. The aim is to determine whether or not the performance prediction for the current period (i.e. the prediction for a given period t formed before the end of the period) has a systematic bias. We will do so by using a statistical test developed by Brown and Matial (1981). We find in our analysis that the results are severely affected by outliers. Therefore, in the sequel of the paper we will pay special attention to the effect of outliers and we will also compare two different techniques to identify such outliers.

2. The Test.

When comparing predicted with realized values of a given variable we say an expectation is rational in Muth's sense if "they are equal to the true mathematical expectation conditioned on all relevant information known at the time forecasts were made" (Evans and Gulamani, 1984, p. 3). This means that "rational" expectations have to satisfy certain conditions. The version of the rational expectations hypothesis becomes weaker as more conditions are violated.

The first of these conditions is orthogonality (Anderson and Goldsmith, 1994, p. 383). This means that all available (relevant) information has been used in an optimal manner. Since it is impossible to know *all* available information, there is no test available to test for orthogonality or "full rationality" (see, Brown and Matial, 1981, p.493). The assumption of full rationality can be weakened to partional rationality. This means that the information used, though not complete, is efficiently used; this is the second, efficiency condition. Partial rationality implies under certain conditions full rationality (Brown and Matial, 1981, p. 494). It is however very difficult, not to say impossible, to determine which information has actually been used by entrepreneurs. Again we can weaken the assumption. The third condition is that of noncorrelation of forecast errors (Anderson and Goldsmith, 1994, p. 383). This means that the previous error is information that should be used when the next forecast is made. If we would regress the forecast error on its past values, the coefficients should not differ significantly from zero. The final condition is that of unbiasedness; the weakest form of the rational expectations hypothesis (Anderson and Goldsmith, 1994, p. 383). Following Theil (1966) we can test for unbiasedness of the prediction (i.e., absence of systematic errors) by estimating the following equation

$$(1) \qquad Y_t = \alpha + \beta \cdot Y^p_{t-k} + u_t \, , \; (k=1,2,\ldots,n)$$

where Y_t is the realization of a variable at period t, Y^p_{t-k} is the prediction for period t formed at time period t-k and u_t is a disturbance term. If we reject the joint hypothesis $\alpha=0$, $\beta=1$, the prediction is said to be biased, and as a result the hypothesis of partial (and full) rationality has to be rejected. This means that systematical errors are made in the predictions[1].

Brown and Matial (1994, p. 495) discuss a problem that is inherent in equation (1); the u_t's are likely to be serially correlated because we cannot rule out the possibility that the unknown future forecast errors are correlated. They show that a disturbance which is serially correlated of an Moving Average-type is quite consistent with both partial and full rationality (they also show that the disturbance term u_t is serially correlated of an MA-type).

In this paper we will try to determine whether or not the investment predictions for the current period (made in the current period) are biased. We will base our estimation on equation (1), but now Y^p_{t-k} is the prediction for period t formed before the end of period t (and hence k=0). Therefore, we obtain (adding subscript i to identify firms)

$$(2) \qquad Y_{i,t} = \alpha + \beta \cdot Y^p_{i,t} + u_{i,t}$$

The last "prediction" which we can investigate is the "prediction" made in the preceding period (we need to know the "true" investments). We do not have serially correlated u_t's because we are not confronted with unknown (future) forecast errors in equation (2). So if we find that the u_t's are serially correlated the entrepreneurs did not fully use the information contained in the past forecast errors (see Anderson and Goldsmith, 1994, p. 383). We will test for autocorrelation by means of a Chi-square test.

Blomqvist (1989) tested for a "learning effect". The issue of

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[1] That is, the prediction is not equal to the mathematical expectation of the realization, conditional on the prediction.

learning is particularly relevant in the case evidence against the rationality hypothesis is found because the test for learning will reveal whether this departure from rationality is temporary or permanent. When the hypothesis of unbiasedness is rejected, we will test whether the bias decreases over time. In case entrepreneurs make systematic errors (a bias), it is interesting to see whether the errors decrease over time. We say the entrepreneurs are "learning" when predictions are biased but the bias decreases over time; that is, improving the forecasts gradually to an outcome consistent with rational expectations.

Given our database (see section 3) we are able to estimate equation (2) for each year from 1986 until 1994. In addition, we can estimate equation (2) using longitudinal data (using the same group of firms over eight years). We notice that the prediction variable in our model is not a "genuine" prediction; it is partly a realization and partly a prediction[2]. Since we have to compare the predictions with the realized investments, we have to construct panel datasets of firms followed over at least two years.

3. Data.

The data used in our analysis originate from a survey held each year (during the months September-November) among Dutch firms by the Chambers of Commerce. The questionnaire contains questions about the past years' realizations and expectations for the current year and the next year. The expectations for next year are qualitative variables. The questions concern employment, output, investment and profit.

All firms with more than 50 employees are interviewed each year. Furthermore, about 70% of the firms with less than 50 employees are interviewed. Detailed micro data on three regions are available: Amsterdam and Utrecht (two central regions) and Den Bosch (in the intermediate zone), for the years 1986-1994.

To be able to confront the expectations for the current year with the realizations (which are not known until some time in next year), we

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[2] As a result, we could also argue that it is (partly) investigated whether the reported values have a systematic bias. In this interpretation, the finding of a bias would point at systematic misjudgements of enterpreneurs when reporting investment levels. For example, in large firms this failure may be due to the malfunctioning of information flows through the firm. Alternatively, firms may deliberately under- or overestimate investments for strategic reasons.

need to match two successive surveys. It turns out that a firm has a chance of about 50% to be present in two successive surveys (there is a response rate of about 70%; new firms emerge and other firms quit). A group of 470 firms are present in all surveys from 1986 until 1994. Since these 470 firms need not be representative for the sample in every year, we need to estimate also equation (2) for each year separately.

Table 1 shows the average value (in thousands Dutch guilders) and the standard deviation for the prediction error of the firm investments (expectation minus realization). It turns out that (apart from 1993) the realization is always higher than the expectation, indicating an underestimation of the current investments (see also Gorter, Nijkamp and Rienstra, 1995). On the other hand, the standard deviation is of such a scale that we cannot speak of significant differences between the averages. There are however some outliers, extremely high expectations (realizations) with low realizations (expectations). We will return to this issue later on. In 1993 the mean prediction error is positive; the entrepreneurs were apparently rather optimistic as a group. Maybe as a result of this phenomenon, the prediction error is negative again in 1994 and the difference between realization and expectation has never been as large as in 1994 (in absolute value). The 470 companies which can be observed over all eight years have an average expectation (the mean over all companies and years) which is higher than the realization. Notice also that this number is considerably higher than the mean in each year due to the overrepresentation of large firms in the longitudinal dataset.

4. Estimation Results.

In our statistical analysis, we first estimated equation (2) for *all* companies (see Table A1, Appendix 1). We tested for heteroscedasticity (and in the case of the longitudinal data also for autocorrelation). It turns out that the size of the company (measured by the number of employees) causes certainly heteroscedasticity. In most cases there are no specific regional or sectoral influences. We therefore estimated equation (2) for small and large (more than 50 employees) firms separately (It is noteworthy that Van den Ende and Nijkamp (1995) and Gorter, Nijkamp and Rienstra (1995) also found the size of the firm to be influential).

In tables 2 and 3 the results of the statistical experiment are presented. Both the separate hypotheses ($\alpha = 0$ and $\beta = 1$) and the joint hypotheses ($\alpha = 0$, $\beta = 1$) are rejected in all cases. In most cases α is significantly larger than 0, while ß is significantly smaller than 1. In the longitudinal analysis heteroscedasticity appears to remain for large firms[3], and for small companies the disturbances are serially correlated. The latter finding implies that enterpreneurs in small companies - included in the longitudinal dataset - did not fully use the information in the past forecast errors. In other words, information exists which, if used, could have reduced the forecast error. Using the longitudinal datasets, we tested whether there was a "learning effect". If such an effect were to be found, we would expect it with the larger companies, since we found autocorrelation in the disturbance term with the smaller companies (indicating that not all information from past forecast errors was (fully) used). In table 4 we see that small firms clearly do not learn over time whereas for large firms a weak tendency towards learning is observed (the effect is negative, but not significant at the 5%-level).

So on the basis of the t- and F-tests presented in the above tables (and the LM(H) test in table 3) we may conclude that the expectations on investments are biased. Furthermore, with the longitudinal datasets we do not find any indication that the bias reduces over time. Hence, we do not find evidence of a "learning effect". One can wonder what causes this bias. There are several possibilities. First, the persons responsible for the answers given in the survey might simply not be able to produce accurate predictions due to malfunctioning of information flows through the firm. The systematic bias and absence of a learning effect would be the result of permanent malfunctioning[4]. Second, they may give "false" predictions as a form of strategy, but then one can wonder what would be the gain to the entrepreneurs. On the other hand, the absence of a learning effect and the systematic bias would support this idea to some extent.

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[3] We tested for heteroscedasticity using sectoral differences as a possible cause. we observe six sectors: agriculture, industrial, construction, wholesale, retail and services. We also tested for heteroscedasticity using regional differences as a possible cause. These did not prove to be significant. the latter test is not reported in tables 2 and 3.

[4] It is questionable whether this explanation is applicable for small firms since the person filling the questionnaire might also be the owner of the firm.

Table 1, Mean and standard deviation of the prediction error of investments[a)].

	1987	1988	1989	1990	1991	1992	1993	1994	87-94
prediction error	-2.60 (2016)	-32.88 (1776)	-5.30 (2397)	-28.65 (2663)	-8.35 (1733)	-5.53 (1351)	10.72 (1700)	-82.03 (8382)	87.64 (3152)
observations	2564	3341	3403	3685	4217	4792	3962	3667	3760[b)]

a) Standard deviation between parentheses. The average values are influenced by economic development, sample size and the composition of the sample (with respect to sectors), so they cannot be seen as longitudinal series.
b) There are 470 companies which can be followed for eight years, so there are 3760 observations.

Table 2, Estimation results, small companies[a)].

	86	87	88	89	90	91	92	93	86-93
α	117.83 (15.85)*	53.14 (6.42)*	154.71 (39.79)*	120.14 (30.14)*	19.59 (12.36)	52.92 (12.95)*	10.22 (8.62)	50.42 (9.83)*	95.64 (14.75)*
β	0.29 (0.01)*	0.84 (0.01)*	0.23 (0.05)*	0.47 (0.05)*	1.03 (0.01)*	0.72 (0.01)*	0.95 (0.01)*	0.62 (0.01)*	0.60 (0.02)*
R^2	0.19	0.70	0.01	0.03	0.82	0.42	0.83	0.73	0.21
n	2032	2784	2826	3042	3546	4130	3383	3072	2480
LM(H)	15.64**	14.74	3.70	5.39	4.87	8.54	9.36	18.68**	8.12
LM(SC)									9.86*
F	1426.24*	137.20*	102.78*	49.71*	10.29*	230.64*	20.79*	1639.98*	151.46*

a) standard error in parentheses. * significant at 5%, we test $\alpha = 0$ and $\beta = 1$. LM(H) is a test for heteroscedasticity with sectoral differences as a possible cause. There are 5 degrees of freedom, $\text{chi-square}_5^{0.05} = 11.07$. LM(SC) is a test for (first order) autocorrelation with one degree of freedom, $\text{chi-square}_1^{0.05} = 3.84$. F is a test with the joint hypothesis $\alpha = 0$, $\beta = 1$.

Table 3, Estimation results, large companies[a)].

	86	87	88	89	90	91	92	93	86-93
α	627.62 (131.24)*	271.33 (187.98)	333.29 (105.20)*	389.98 (204.46)	397.83 (148.45)*	195.08 (117.29)	247.17 (175.20)	966.23 (866.83)	530.05 (127.23)*
β	0.74 (0.01)*	0.90 (0.03)*	0.81 (0.01)*	0.85 (0.02)*	0.81 (0.02)*	0.93 (0.01)*	0.91 (0.01)*	0.90 (0.05)*	0.80 (0.01)*
R^2	0.86	0.70	0.94	0.79	0.76	0.87	0.90	0.38	0.87
n	532	557	577	643	671	662	579	595	1280
LM(H)	6.44	5.34	10.32	10.32	8.54	6.62	3.68	6.38	19.71*
LM(SC)									0.05
F	197.12*	7.88*	248.84	36.15	62.39*	13.82*	29.59*	2.64**	289.68*

a) standard error in parentheses. * significant at 5%, we test $\alpha = 0$ and $\beta = 1$. LM(H) is a test for heteroscedasticity with 5 degrees of freedom, $\text{chi-square}_5^{0.05} = 11.07$; LM(SC) is a test for (first order) autocorrelation with one degree of freedom, $\text{chi-square}_1^{0.05} = 3.84$. F is a test with the joint hypothesis $\alpha = 0$, $\beta = 1$.

Table 4, Test for a "learning effect"[a) b)].

	small	large
constant	452.99 (566.80)	11189.90 (5685.19)
trend	-3.62 (6.33)	-110.54 (63.44)
n	310	160

a) dependent variable : forecast error;
explanatory variables : constant and a linear trend term (t).
b) standard error between parentheses.

Third, the entrepreneurs may simply give a wild guess due to a lack of interest or cooperation. We do observe some cases where expected investments worth hundreds of millions are reported, while realized investments are virtually zero. In the next section we will discuss these (and less extreme) cases or outliers and their impact on the estimation results in more detail.

5. The Impact of Outliers.

Gorter, Nijkamp and Rienstra (1995) who analyzed investment data on a aggregate level found that outliers had a strong influence. The outliers can be identified by using one of the following two methods, which will be described briefly.

The first method identifies outliers on the basis of the explanatory variables in the model (the so-called hat matrix, see for more details, Krasker et al., 1983). We know, before we perform our analysis, that some of the data are flawed; for example typing errors or information that is deliberately held back will (almost certainly) affect the outcomes in our dataset. There are, for example, firms who report to invest several hundreds of millions, while in the end no investment appears to be made (or vice versa). To check for the influence of these (extreme) data points (expectations of several hundreds of millions versus zero realizations or vice versa), we identify these leverage points (or influential X-data) on the basis of the diagonal of the hat matrix $H = X(X'X)^{-1}X'$, where X is the data matrix with n observations and p explanatory variables. Data points are said to be influential if the diagonal element $h_i > 2 \cdot p/n$, where i is the number of the row of X under consideration (see Krasker et al., 1983). Note that in our application, we have only one X-variable namely Y^p.

A second method of identifying outliers is on the basis of (standardized) residuals. The advantage is that we do not, like in the previous method, identify the really large values of the explanatory variables as outliers. For example, a firm which reports to invest a hundred million might be identified as an outlier (no matter the realization), while a firm which reports fifty thousand but invests a hundred million might not be identified as an outlier (on the basis of the hat matrix). On the basis of the (standardized) residuals those firms are identified as outliers which have substantial differences between the expectation and realization. The drawback is that we estimate the model and identify those firms which have the poorest fit as outliers, even though they might contain valuable information.

We estimated equation (2) with the identified outliers excluded[5]. The outliers identified by the first method proved to have a considerable effect; only a few outliers were detected each year, but the estimates changed considerably; α moved closer towards 0 and β moved closer towards 1. But still, in most cases both the separate and joint hypothesis did apparently not hold.

When we estimated the model without the outliers identified by the second method, the results did also change somewhat, but not as much as in the previous case. The estimated α moves closer towards 0, the estimated β does not change substantially.

The two different methods of identification lead to totally different estimation results. The first method of identifying outliers labels an observation as an outlier, if $h_i > 2 \cdot p/n$. The (really) large values of Y^p_t are identified as outliers (see Table A2, Appendix 1). In some cases this can be true; there are firms that report to invest hundreds of millions but invest (almost) nothing. Perhaps these firms may deliberately give wrong information or have no insight into their investments in the current period. On the other hand, there are companies that report to invest on a large scale and do so. These are (wrongly) identified as outliers because this identification method only looks at Y^p_t and therefore cannot distinguish between "false" (with both extreme predictions and realizations) and "true" (with only extreme predictions or observations) outliers. So this method identifies firms as outliers when the

[5] Detailed results are available from the authors on request.

reported investments are large and largely exceed the realized investments, but occasionally also firms with large reported investments and zero forecast error.

The second method of identification first estimates equation (2) and then uses the residuals to identify the outliers. It turns out that both small and large values of Y^p_t are identified as outliers. In most cases, the difference between Y_t and Y^p_t is quite substantial (see also Table A2, Appendix 1).

In Figure 1 we show (in a simplified way) what happens with our estimation results when we use either method I (forward identification) or method II (backward identification). Line A is an estimation using a full data set for a particular year. If we use method I to identify outliers (forward identification), values of Y^p_t that exceed the dotted line I are identified. If we re-estimate with the exclusion of these outliers the estimated slope will go up and the constant will drop[6]. The second method identifies those companies as outliers that have Y_t above the upper dotted line II or beneath the lower dotted line II. As a result, only the constant changes significantly. The forecast error of the firms identified by the second method as an outlier is in most cases negative (points in the upper part of the cloud, indicating an under-estimation) and as a result the estimated line moves down.

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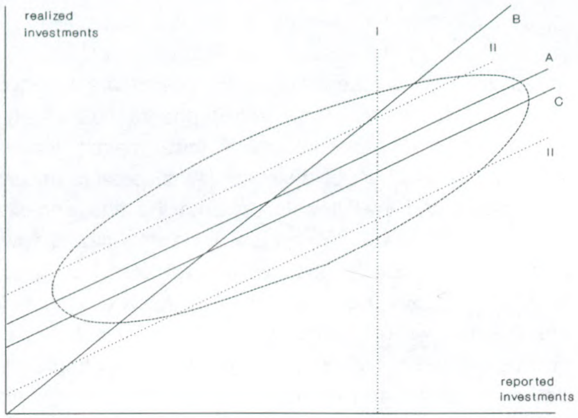
[6] In Table A2, appendix 1, we see that the value of Y^p_t of the outliers identified by the first method is on average higher (as the values of Y_t and the average value of Y^p_t identified by the second method).

Figure 1, Graphic interpretation of the identification methods[a)].



a) Line A is an estimation using the full data set. The dotted lines I and II show the selection made by the two identification methods. Line B is the estimation using identification method I, line C is the estimation using identification method II.

6. Conclusion.

In this paper we have tried to determine whether or not the entrepreneurial expectations for current investments are biased. The overall conclusion is that the expectations are clearly biased and that this bias exhibits a permanent nature. Outliers do affect the estimation results to a large extent, but the conclusion does not fundamentally change when we estimate our regression model with the outliers excluded. Two methods were used to identify the outliers. Both methods have their advantages and their drawbacks. The first method tries to identifies firms with extreme values of Y^p_t as outliers. This seems to be appealing, but in our case only the high extreme values are identified, and these predictions do not always appear to be that poor. The second method selects both small and large values of Y^p_t as outliers. The disadvantage is that we first estimate equation (2) and identify those firms as outliers which give the poorest fit. Both methods however do not affect our conclusion: predicted (or reported) investments are systematically biased and hence the results for the entrepreneurs do not show that they behave rationally in the way described above.

The bias is not affected by a learning effect, or in other words, entrepreneurs do not improve on their predictive capabilities. This poses another question: is the bias the result of the entrepreneurs' failure to come up with "good" predictions (in the sense that the overall prediction error is not significantly different from zero) or do entrepreneurs deliberately give false predictions ? For the entrepreneurs' sake (and maybe for the national economy's sake) we hope it is not their inability to provide accurate figures; otherwise expectations and investments on both the firm and sectoral level would be based on biased expectations and false information flows. Anyway, using these investment expectations as an indication of "entrepreneurial confidence" and the well-being of, for example, a sector would be risky, to say the least. Consequently, we recommend the use of other indicators such as expectations on output or employment to signal the firm's future performance. These variables are expected to behave more smoothly and therefore are less likely to exhibit a systematic bias. Further research however should reveal whether this appears to be a fruitful approach.

References

Anderson, M.A. and A.H. Goldsmith (1994), Rationality in the mind's eye: An alternative test of rational expectations using subjective forecast and evaluation data, *Journal of Economic Psychology*, 15, 379-403

Blomqvist, H.C. (1989), The "rationality" of expectations: An experimental approach, *Journal of Economic Psychology*, 10, 275-299

Brown, B.W. and S. Maital (1981), What do economists know ? An empirical study of experts' expectations, *Econometrica*, 49, 491-504

Ende, M van der, and P. Nijkamp (1995), Industrial Dynamics and Rational Expectations in a Spatial Setting, in: Bertuglia, C.S., M.M. Fisher and G. Petro (eds.), *Technological Change, Economic Development and Space*, Springer Verlag, Berlin/Heidelberg, 238-253

Evans, G. and R. Gulamani (1984), Tests for rationality of the Carlson-Parkin inflation expectations data, *Oxford Bulletin of Economics and Statistics*, 46, 1-19.

Gorter, C., P. Nijkamp and S.A. Rienstra (1995), Space-Time Dynamics of Investments, mimeo, Department of Regional Economics, Free University Amsterdam

Krasker, W.S., E. Kuh and R.E. Welsch (1983), Estimation for Dirty Data and Flawed Models, in: *Handbook of Econometrics* (eds. Z. Griliches and M.D. Intriligator), I, 651-698.

Theil, H. (1966), *Applied economic forecasting*, Amsterdam: North-Holland.

Appendix 1.

Table A1, estimation results, all companies[a)].

	86	87	88	89	90	91	92	93	86-93
α	174.65	79.57	117.78	117.71	91.40	48.65	48.25	161.02	209.70
	(24.52)*	(30.71*)	(37.60*)	(42.58*)	(25.54*)	(19.35*)	(26.04)	(138.54)	(43.71)[8]
ß	0.73	0.91	0.80	0.85	0.84	0.91	0.91	0.90	0.80
	(0.01)*	(0.01)*	(0.01)*	(0.01)*	(0.01)*	(0.01)*	(0.00)*	(0.02)*	(0.00)*
R^2	0.83	0.72	0.77	0.73	0.78	0.83	0.90	0.40	0.87
n	2564	3341	3403	3685	4217	4792	3962	3667	3760
LM(H)	28.84*	25.99*	4.59	22.60*	33.54*	35.58*	51.42*	16.76*	48.62*
LM(SC)									2.54
F	836.34*	46.33*	356.60*	144.86*	244.80	102.69*	181.99*	16.11*	800.39*

a) standard error between parentheses. significant at 5%, we test $\alpha = 0$ and $ß = 1$. LM(H) is a test for heteroscedasticity with 5 degrees of freedom, $\text{chi-square}_5^{0.05} = 11.07$. LM(SC) is a test for (first order) autocorrelation. F is a test with the joint hypothesis $\alpha = 0$, $ß = 1$.

Table A2, Average values of identified outliers, small companies[a)].

	method	86	87	88	89	90	91	92	93
Y^p_t	I	7710	2733	3934	2984	8087	5451	8857	15936
Y_t		3951	2361	1690	1872	6620	4336	7170	9247
Y^p_t-Y_t		3759	372	2245	1112	2067	1115	1687	6689
cases		14	45	35	57	21	45	24	11
Y^p_t	II	6425	1180	464	4403	5811	7473	6447	9183
Y_t		6409	2835	34677	19075	7371	9143	6006	7133
Y^p_t-Y_t		16	-1655	-34213	-14673	-1560	-1670	441	2049
cases		13	31	4	7	27	21	24	18

a) method I: forward identification, method II: backward identification.

Average values of identified outliers, large companies[a)].

	method	86	87	88	89	90	91	92	93
Y^p_t	I	70000	38649	90002	80686	36364	33611	84813	112051
Y_t		54641	32222	75749	59735	28251	33997	74053	96588
Y^p_t-Y_t		15359	6427	14253	20952	8103	-387	10760	15463
cases		6	12	6	8	17	21	12	12
Y^p_t	II	15029	36964	48873	37652	35983	32314	61789	4000
Y_t		22048	41010	46660	43962	36724	37085	56651	500000
Y^p_t-Y_t		-7018	-4047	2212	-6310	-741	-4771	5138	-496000
cases		13	6	9	9	9	11	14	1

a) method I: forward identification, method II: backward identification.

Ontvangen: 05-06-1996
Geaccepteerd: 02-10-1996