DNB WORKING PAPER

On the predictability of GDP data revisions in the Netherlands

Olivier Roodenburg

No. 4/July 2004

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* I am especially grateful to prof. dr. J.F. Kiviet, Marga Peeters and Ard den Reijer for their comments and suggestions. I would also like to thank Peter Vlaar, and the participants of the DNB Lunch Seminar of the 9th of December 2003 for their comments, and Peter Keus for statistical assistance. Moreover, I would like to thank the CBS for their comments on an earlier version of this paper.
Views expressed are those of the individual authors and do not necessarily reflect official positions of De Nederlandsche Bank.

Olivier Roodenburg had an internship at de Nederlandsche Bank from September until February 2004 under the supervision of dr. H.M.M. Peeters and drs. A.H.J. den Reijer (Research Divsion, DNB) and prof. dr. J.F. Kiviet (University of Amsterdam). This Working Paper is an abbreviated version of his master's thesis.

Working Paper No. 004/2004

July 2004

De Nederlandsche Bank NV
P.O. Box 98
1000 AB AMSTERDAM
The Netherlands

ABSTRACT

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The first part of this paper is based on a study by Faust, Rogers and Wright (2004). They found some evidence of predictability of GDP revisions for the G-7 countries, especially for the UK, Italy and Japan. In this paper we investigate the quality of the first Dutch GDP releases by using the same technique. Our findings suggest that Dutch GDP revisions are also predictable to some extent. These results are strengthened when applying the more general state-space estimation procedure. The state-space model is used to estimate the final or unobserved data, given the preliminary or observed data.

Key words: Preliminary data, final data, revision, GDP, state-space model, Kalman filter
JEL codes: C12, C13, C22, C53

1 INTRODUCTION

Every quarter Statistics Netherlands (CBS) releases new estimates of gross domestic product (GDP) in the Netherlands. Data revisions between the time that the CBS makes its initial and final estimates of GDP are numerous. Preliminary estimates are always available soon after the appropriate quarter, but these estimates may contain some measurement error and may differ from the final data. Therefore macroeconomic forecasts may be affected strongly when they are obtained from preliminary data. So, the quality of the preliminary data is of importance for the quality of the forecasts.

Data revisions are distinguished by two polar characterisations introduced by Mankiw and Shapiro (1986), namely the noise and the news characterisation. Under the noise characterisation revisions are biased, so that the revisions are correlated with the preliminary estimates. The preliminary estimates contain information which would be useful in predicting forthcoming GDP revisions. In contrast with the noise characterisation, revisions are unbiased in the news characterisation. GDP estimates released after the preliminary estimates reflect news, thus there is no correlation between the preliminary estimate and the revision term because the estimate contains all available information. Forecast rationality tests are applied to distinguish between these two characterisations.

Many studies investigated the size of revision errors, e.g. Faust, Rogers and Wright (2004). In G-7 GDP announcements they found some evidence for the predictability of GDP revisions for the UK, Italy and Japan. Palis, Ramos and Robitaille (2003) studied Brazilian GDP revisions and also found some evidence that revisions are predictable. Mankiw and Shapiro (1986) did already some earlier research and concluded that the revisions for US GNP are more or less unpredictable. York and Atkinson (1997) analyse the behaviour of revisions for the seven largest OECD countries and they found that revisions for GDP growth were large but not significantly different from zero, so there was no systematic bias in the preliminary national accounts figures.

Kazemier and Van Rooijen (2002) investigated a wider set of national accounts statistics using a broad range of attributes that make up for the quality of a statistic. They stress, amongst other things, that there exists a trade-off between reliability and timeliness of publication. Reliability is the extent to which provisional estimates predict final estimates. Therefore, a reliable statistic is one for which the difference between the preliminary and the final estimate, that is the revision, is uncorrelated with the preliminary estimates. A preliminary estimate is reliable if it represents the final estimate well, even if the final estimates are wrong. Accuracy refers to the extent to which the final estimate of a statistic describes reality. The focus of this paper is solely on the reliability of Dutch GDP figures.

Swanson and Van Dijk (2001) examined the entire revision process for seasonally adjusted and unadjusted industrial production and the producer price index. For these data series they found evidence of structural breaks taking into account whether there was a recession or an expansion. It turned out that reporting agencies over-state and under-state the estimates in a recession and an expansion, respectively, because they do no want to reinforce the direction of the business cycle. Moreover they found strong evidence of predictability in the subsequent revisions according to the asymmetry just mentioned.

Real GDP gives a very good summary of economic performance. It is often considered as the best measure of how well the economy is performing. This statistic is of great interest for researchers and policymakers. They care not only about the economy's total output of goods and services but also about the components of this output. The national income accounts divide GDP into five broad categories of spending: consumption, investment, government purchases, exports and imports. The national accounts identity equals the sum of the first four components, subtracts imports and adds the change in inventories. All these measures exhibit a regular seasonal pattern, reaching a peak in the fourth quarter and then falling in the first quarter of next year. Researchers often want to eliminate the fluctuations due to seasonal changes, when they study GDP.[1]

The first estimate of quarterly GDP in the Netherlands is released by CBS after about 45 days and this is the so-called flash estimate. These estimates are released by many countries as they provide a good first overview after the end of the reference quarter. CBS introduced the flash estimate in 1991 which was released in about 56 days after the appropriate quarter. In 2001 this period was cut to 45 days. A disadvantage of a fast first estimate is that it is based on incomplete information. CBS has limited information on some components of GDP at the time of publication, especially on the service sector. Forecasting has been the only possible way of including this component of GDP in the flash estimate (Shearing, 2003). Nevertheless it is a very popular measure, because it is used to monitor the phases of the economic cycle and many central banks and businesses take advantage of these estimates for their future decisions. Furthermore, the lack of information is replaced by judgmental adjustments, which involve assumptions about the likely values taken by specific GDP components. Around 60 days after the flash estimate CBS produces a regular estimate and this is supposed to be better, as more information has become available. The difference between the flash and the regular estimate is called a revision or an information based revision. There are also structural data revisions due to the structure of the economic data accounting system, such as changes in aggregation method or estimation method,

[1] This is mostly done by using an X-11 method, but the precise procedures are too elaborate to describe in full detail in this paper.

changes in base years and changes in definitions. A change in the definition of GDP alters the behaviour of the estimated GDP series relative to a former definition, an example is the European System of Accounts (ESA95) which increases the level of GDP because for example intangible fixed assets such as software are included.

In this paper, we want to test whether GDP revisions in the Netherlands are predictable for quarterly observations. The study made by Faust, Rogers and Wright (2004) finds some evidence of predictability of revisions for the UK, Italy and Japan. Here, we explore the quality of the first Dutch GDP releases by using the same technique. In our analysis the first regular release is used. The flash estimates are not considered as the sample period is quite short. Furthermore, we investigate the issue of predictability for GDP, given the preliminary data and the revised data. This study is based on the article written by Mariano and Tanizaki (1995). They take account of measurement noise to obtain efficient forecasts and apply state-space techniques and the Kalman filter for the prediction of US per capita consumption data.

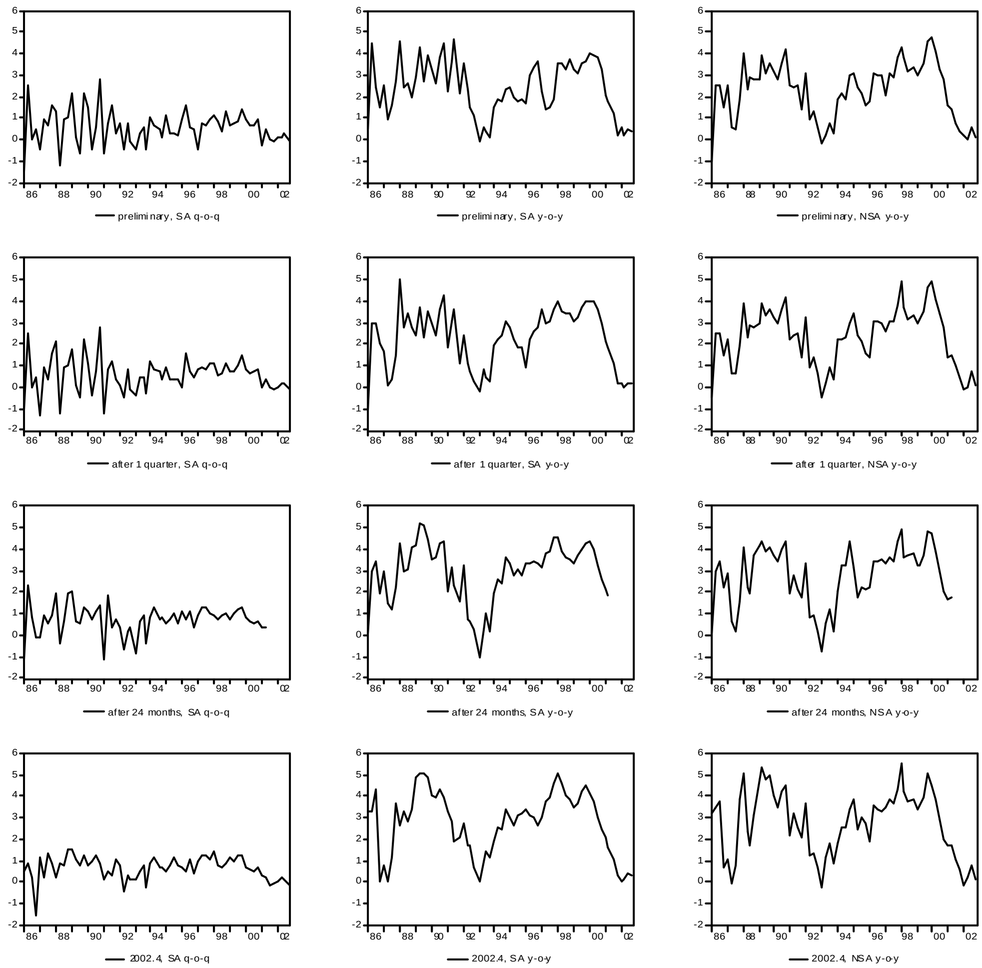
The paper is structured as follows. Section 2 describes our data. In section 3 we present the econometric model and introduce some mathematical notations. In addition we describe the estimation process and discuss the estimation results. Section 4 presents the state-space model and the estimation results based on this approach. Finally, section 5 makes a number of comments and presents the most important conclusions.

2 DATA

Quarterly data for GDP growth rates are gathered from CBS publications and run from 1986 to 2002 (68 quarters). CBS began to report quarterly GDP from 1985 onwards, but we start our data set in 1986. The reason will be discussed below. In 1999 Statistics Netherlands released for the first time GDP according to the European System of National Accounts 1995 (ESA95). The ESA95 implied shifts in concepts, methods, definitions and classifications. ESA95 achieves a harmonisation of the national accounts for the 15 European Union member states as requested by Eurostat in accordance with EU regulation. In our view, the adoption of ESA95 will not have any serious implications because we consider the sum of all the components, namely GDP, and we are using growth rates so that a level shift is only one outlier.

We use both seasonally adjusted data (SA) and non-seasonally adjusted data (NSA). The only available published data are the SA growth rates, which are defined as the quarter-over-quarter (q-o-q) percentage change, and the NSA growth rates, which are defined as the year-over-year (y-o-y) or the four-quarter percentage change. Let x denote growth rates, then growth rates q-o-q and growth rates y-o-y are computed as $100 \cdot \left(GDP_t - GDP_{t-1}\right)/GDP_{t-1}$ and $100 \cdot \left(GDP_t - GDP_{t-4}\right)/GDP_{t-4}$ respectively. The q-o-q growth rate compares the level of GDP in one quarter to the level of GDP in the previous quarter and the y-o-y growth rate compares it to the same quarter of the previous year. The latter measure is a very popular measure, because it avoids seasonal variations (it is an implicit seasonal adjustment process) and it looks at what happened to the economy over the entire previous year. Furthermore, this measure is easier to compare among countries, because the derivation is straightforward. For SA series q-o-q it is not always clear which seasonal adjustment procedure has been used and whether it is adjusted for working days. That makes it harder to compare. The y-o-y growth rate also has some disadvantages. First of all, it is not corrected for differences in working days. For example, in 2004 the leap year adds an extra working day to the end of February. Christmas and Boxing Day fall on weekend, so they will increase the number of working days this year compared with 2003 and these extra working days could result in a higher growth rate. Germany has even five extra working days this year. Secondly, y-o-y growth rates are not corrected for a base effect. This means that when in a particular quarter the growth rate shows an unprecedented high level and in the subsequent year the appropriate quarter reaches a more normal level, then the growth rate will decline strongly. Last but not least, compared with the q-o-q growth rates it is slow in the identification of turning points. Besides these two series we have used a method which creates the SA growth rates as the y-o-y percentage change, because we want to know how these series behave in relation with the available two data series[2]. This derivation omits the first three quarters of 1985, hence we decided to start from 1986. We have not constructed the NSA growth rates q-o-q, because it was too difficult to implement a seasonal pattern. The growth rates are represented in Figure 1 to give a first impression of how the series change over time. The Tables I, II and III in Appendix A show the raw data that we have used in our analysis.

Figure 1 Original GDP growth series



Explanation: The first row shows growth rates for the preliminary estimates, the second row the revised estimates after 1 quarter, the third row revised estimates after 24 months and the last row shows final estimates, that is the estimates in 2002.4. E.g. in the top left figure the GDP growth rate in 1986.1 is the first estimate of the Dutch GDP growth rate, in the second row 1986.1 indicates the estimate released in 1986.2. In the third row 1986.1 illustrates the estimate released after 24 months, that is in 1988.1 and for example 1988.3 illustrates the estimate released in 1990.3. In the bottom row the GDP growth rates for every period are the estimates released in 2002.4.

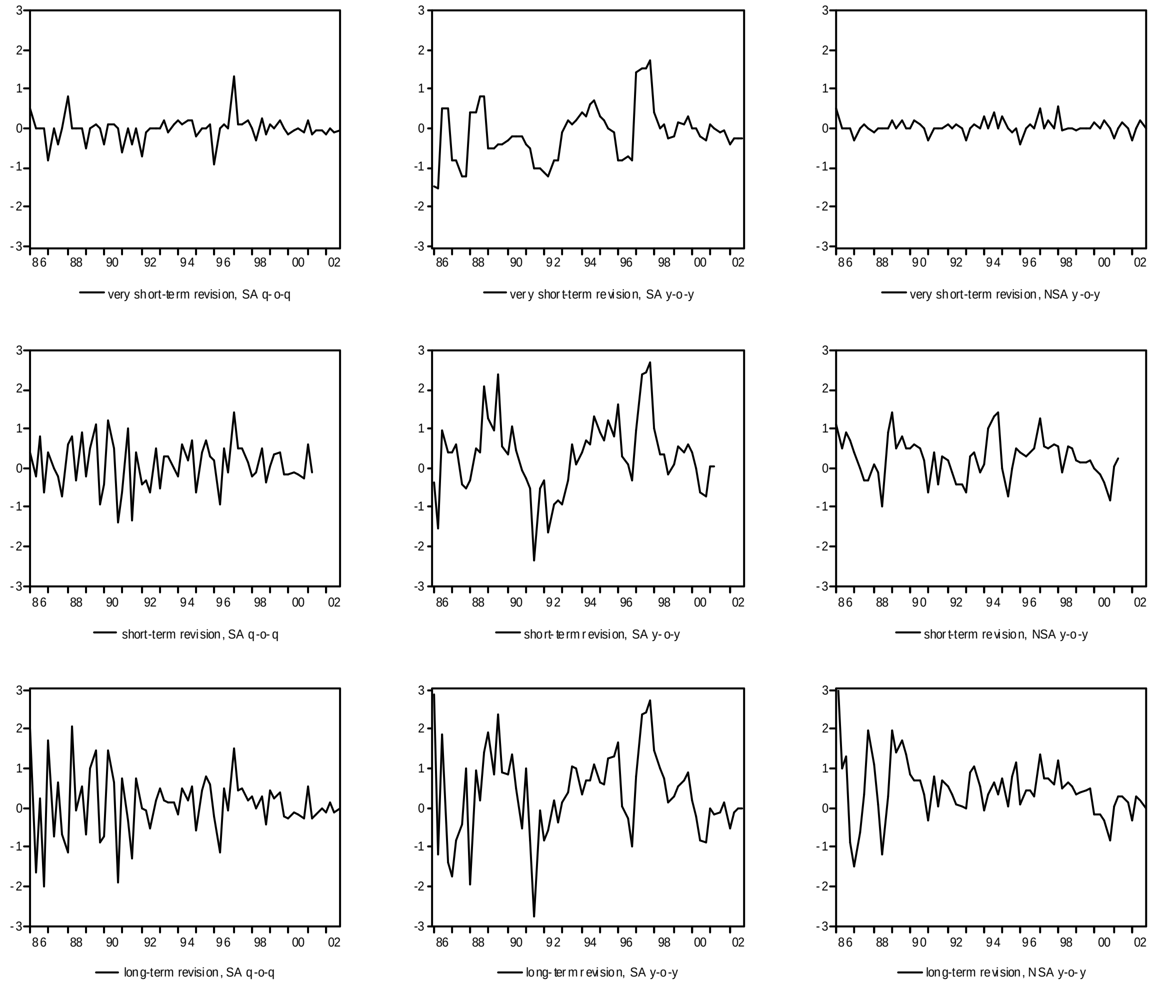
[2] We have made an index for our given SA growth rates q-o-q with base year 1984.4, thus our first computed growth rate y-o-y, $100 \cdot \left(GDP_t - GDP_{t-4}\right) / GDP_{t-4}$, starts from 1985.4.

Following Faust *et al.* (2004) we compute a short-term and a long-term revision and we add a very short-term revision. The paper of Palis, Ramos and Robitaille (2003) also includes a very short-term revision; this is due to their small sample size. First of all, the first published figures are used to construct the preliminary data for GDP growth. Then the very short-term revision compares GDP growth based on the preliminary data with the revised estimate one quarter later. The short-term revision is the revision between the preliminary estimate and the revised estimate after a period of twenty-four months. Most of these revisions in between take place when there is additional information. The long-term revision is the revision between the preliminary estimate and the final figure, in our case 2002.4. This revision does not only occur when more information becomes available but also occurs when there are redefinitions, such as changes in the base year. All data series are obtained from CBS. Besides, the sample of the short-term revision is shortened a little bit because the closer we are to the end of the sample period the more the short-term and long-term revisions coincide. Indeed, for 2000.4 the short-term revision and the long-term revision are the same. This problem forced Palis *et al.* (2003) to introduce a very short-term revision. The summary statistics of the revisions are given in Table 1 and the histograms are displayed in Appendix B. In addition the graphs of the several revisions are shown in Figure 2.

In case the preliminary estimate would contain only news and no noise, the means of the revisions should be zero. From Table 1 it follows that the mean and the root mean square error of the long-term revisions are larger than the short-term revisions and the very short-term revisions for all three series. The same holds generally for the standard deviation. The revisions are all positive on average, except the very short-term revision, and this implies that there is a downward bias in the preliminary estimates. So, there is a tendency for pessimism in Dutch GDP announcements. In contrast to the article from Faust *et al.* (2004) we do not report a t-value for testing whether the mean revision is equal to zero, i.e. testing the forecast efficiency hypothesis under the untested assumption of forecast independence, because this test is only valid if the mean and the variance are constant and furthermore the observations should be distributed independently. From Figure 2 we can see immediately that the variance is not constant over time, hence the t-value is an invalid statistic.

Before we test the forecast efficiency hypothesis in Section 3, a first indication can be given from Table 1. The means for the very short-term revision are close to zero, so it seems possible that we shall not reject the hypothesis. The same assessment can be drawn for the SA short-term revision q-o-q and the SA long-term revision q-o-q, because the mean of these revisions is also very close to zero. For the remaining four series, that is the y-o-y short-term and long-term revisions, there is a stronger indication for the presence of bias in these revisions. Closer investigation will show if these presumptions are true.

Figure 2 Revisions



Explanation: Revisions for the very short-term (revision between the preliminary estimate and the revised estimate after 1 quarter) are displayed in the first row of the figure. The revisions for the short-term (revision between the preliminary estimate and the revised estimate after 8 quarters) and long-term (revision between the preliminary estimate and the final figure, in our case in 2002.4) are presented in the second row and the last row, respectively.

Table 1 Summary statistics of the revisions

	SA q-o-q	SA y-o-y	NSA y-o-y
	Very short-term revision 1986.1-2002.4		
Mean	-0.02	-0.13	0.04
Mean Absolute	0.17	0.53	0.10
RMSE	0.30	0.69	0.17
Median	0.00	-0.14	0.00
Maximum	1.30	1.74	0.57
Minimum	-0.90	-1.53	-0.40
Std. Dev.	0.31	0.69	0.17
	Short-term revision 1986.1-2000.4		
Mean	0.09	0.34	0.26
Mean Absolute	0.48	0.77	0.47
RMSE	0.58	0.96	0.53
Median	0.08	0.41	0.30
Maximum	1.41	2.66	1.40
Minimum	-1.40	-2.36	-1.00
Std. Dev.	0.59	0.97	0.54
	Long-term revision 1986.1-2002.4		
Mean	0.09	0.38	0.47
Mean Absolute	0.59	0.90	0.67
RMSE	0.79	1.09	0.79
Median	0.15	0.37	0.41
Maximum	2.06	2.87	4.17
Minimum	-2.01	-2.77	-1.48
Std. Dev.	0.80	1.10	0.80

Note: RMSE stands for root mean square error

3 THE ECONOMETRIC MODEL

An alternative way of studying revisions is based on a simple relationship between the revision of the data (r_t) and preliminary data (x_t^p) and is given by the equation

$$r_t^s = a + b\,x_t^p + u_t \tag{3.1}$$

where a and b are regression coefficients, u_t is the regression error and $r_t^s \equiv x_t^s - x_t^p$, where *s*=*f*, t+8 or t+1 and

x_t^f denotes the final data published in 2002.4,

x_t^{t+8} is the revised estimate after a period of 8 quarters from the preliminary estimate,

x_t^{t+1} is the revised estimate after 1 quarter from the preliminary estimate.

Thus the three subsequent revisions, r_t^s, are equal to

the long-term revision: $r_t^f = x_t^f - x_t^p$,

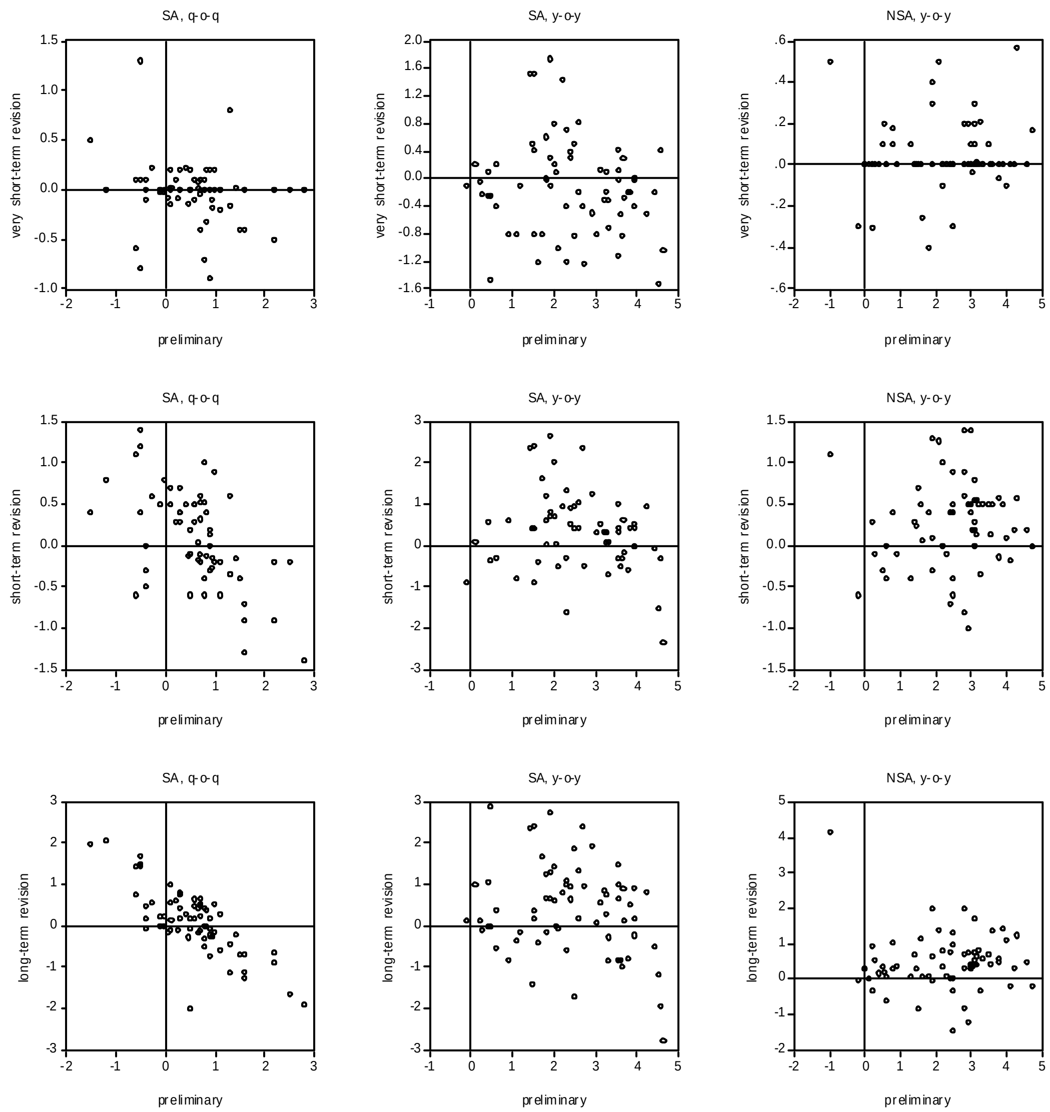
the short-term revision: $r_t^{t+8} = x_t^{t+8} - x_t^p$,

the very short-term revision: $r_t^{t+1} = x_t^{t+1} - x_t^p$.

A test of unbiasedness of the revised data is obtained by testing the hypothesis $H_0 : a = b = 0$ in (3.1). This test is called the Mincer-Zarnowitz forecast efficiency test because it is a test of news versus noise, a test borrowed from the rational expectations theory. In this theory preliminary estimates are considered as different forecasts of the final one, conditional on the available information at the time they are made. If the null hypothesis is not rejected, then the revisions are accepted as unbiased (the news characterisation) so that the revisions and the preliminary estimates are uncorrelated with each other. Thus the news that is released after the preliminary estimates, i.e. revisions, cannot be predicted over time. However, if the null hypothesis is rejected the revisions are biased (the noise characterisation). Then the revisions and the preliminary estimates are correlated with each other. Therefore the estimates contain information, which is useful to predict GDP revisions. Figure 3 shows scatter plots of preliminary GDP growth rates against the very short-term, short-term and long-term revisions which are useful for ascertaining the relationships between the two variables.

According to the rational expectations theory there should be no relationship between preliminary GDP and revisions. The NSA short-term revision y-o-y show a positive relationship between preliminary GDP growth rates and the revisions, that is high preliminary GDP growth rates tend to be revised upward and low preliminary GDP growth rates tend to be revised downward. According to the figures an inverse relationship is characterised by the SA short-term and long-term revision q-o-q.

Figure 3 Relationships between the preliminary GDP growth rates and the revisions



The different scatterplots reveal relationships between the preliminary GDP growth rates and the revisions. As can be seen there is a weak positive relationship for the NSA short-term revision y-o-y. A clear negative relationship can be seen for the SA short-term revision q-o-q and the long-term revision q-o-q.

Estimation by the Mincer-Zarnowitz regression produces the results given in Table 2, where we explain our GDP growth rate revision by the preliminary data only. In Appendix C a proof from Kavajecz and Collins (1995) shows that it is not necessarily true that a rejection of the null hypothesis for the SA data would lead to a rejection of the null hypothesis for the NSA data.

Before testing $H_0: a = b = 0$ we have to analyse the regression errors. Inference from the Mincer-Zarnowitz regression is only allowed if the errors follow a white noise process, that is if $E\left(u_t \middle| x_t^p, I_{t-1}\right) = 0$ where $I_{t-1} = \left(x_{t-1}^p, \ldots, x_{t-h}^p, r_{t-1}, \ldots, r_{t-h} \right)$ for some time horizon h. To check this property Table 2 reports four diagnostic tests, namely the Breusch-Godfrey (BG) Lagrange multiplier test for serial correlation of AR(1) and AR(4) errors, Ramsey's reset test whether the equation is linear or not, White's test for heteroscedasticity (H) and a test for ARCH(1) and ARCH(4) errors. The diagnostics suggest that there is no strong evidence of misspecification in the estimated equations for the SA very short-term revision q-o-q, NSA very short-term revision y-o-y and the SA short- and long-term revision q-o-q[3]. Thus for the remaining five series we can already reject the hypothesis of unbiasedness without using the Mincer-Zarnowitz forecast efficiency test, because $E\left(u_t \middle| x_t^p, I_{t-1}\right) \neq 0$. This already suggests that r_t is not independent of past information.

For the SA very short-term revision q-o-q and the NSA very short-term revision y-o-y the test for $H_0: a = b = 0$ is a valid test and we can see that the null hypothesis has not to be rejected for both series. The two F-statistics for testing $H_0: a = b = 0$ have a p-value of 0.23 and 0.13 respectively and this is much higher than the critical value 0.05. This indicates that the hypothesis of unbiasedness could be accepted. The results for the very short-term revision indicate a reasonably low $\bar{R}^2$ (that is the explanatory power of the regression) so we have to be very careful in our conclusions. For the SA short-term revision q-o-q and SA long-term revision q-o-q we can also use the Mincer-Zarnowitz forecast efficiency test and for both series there is strong evidence that the null hypothesis has to be rejected, because the F-statistics have both a p-value of 0.00. For the SA short-term revision q-o-q the coefficient estimates suggest that an increase in the GDP growth rate by one percentage point leads to a decrease in the revision of 0.40 percentage point in the following quarter. For the SA long-term revision q-o-q an increase in the GDP growth rate by one percentage point leads to a decrease of 0.78 percentage point in the following quarter. The two $\bar{R}^2$ have a value of respectively 0.31 and 0.61. Moreover, only for the SA growth rates q-o-q the $\bar{R}^2$ increases with the length of the revision period. Hence we have strong evidence for predictability for these two revisions.

[3] However only the ARCH LM statistic up to order four is significant at the 5% level of significance for three of them, we do not reject the white noise process of these residuals.

Table 2 Mincer-Zarnowitz regression

	Very short-term revision			Short-term revision			Long-term revision		
	SA q-o-q	SA y-o-y	NSA y-o-y	SA q-o-q	SA y-o-y	NSA y-o-y	SA q-o-q	SA y-o-y	NSA y-o-y
a	0.02	0.06	0.02	0.34	0.78	0.17	0.53	0.90	0.52
	(0.39)	(0.28)	(0.33)	(3.66)	(1.52)	(0.83)	(5.78)	(2.21)	(1.54)
b	-0.07	-0.08	0.01	-0.40	-0.17	0.04	-0.78	-0.22	-0.02
	(-1.32)	(-1.27)	(0.47)	(-4.68)	(-1.08)	(0.52)	(-11.25)	(-1.51)	(-0.16)
F	1.50	1.98	2.12	10.95*	1.56	4.90*	63.75*	2.85	8.98*
p -value	0.23	0.15	0.13	0.00	0.22	0.01	0.00	0.07	0.00
$\overline{R}^2$	0.02	0.01	-0.01	0.31	0.03	-0.01	0.61	0.05	-0.01
Serial correlation LM test									
BG(1)	0.90	0.00*	0.57	0.39	0.00*	0.00*	0.16	0.00*	0.00*
BG(4)	0.24	0.00*	0.80	0.40	0.00*	0.02*	0.11	0.00*	0.01*
Ramsey's reset test									
1 term	0.54	0.07	0.17	0.10	0.00*	0.78	0.65	0.00*	0.03*
2 terms	0.81	0.18	0.20	0.21	0.00*	0.18	0.26	0.00*	0.00*
White heteroscedasticity test									
H	0.37		0.11	0.22			0.71		
ARCH LM test									
ARCH(1)	0.37		0.08	0.10			0.64		
ARCH(4)	0.02*		0.00*	0.14			0.04*		

Notes: The sample begins in 1986.1 and ends in 2002.4 and the short-term revision ends in 2000.4. Newey-West HAC consistent covariance t-values are given in parentheses for the coefficient estimates. We report probability values for the diagnostics. The F-statistic and its p-value are used as a test whether the two coefficients are equal to zero. BG(h) denotes the Breusch-Godfrey test statistic for up to h-th order autocorrelation. H is White's test for heteroscedasticity and Ramsey' s reset test tests whether the equation is linear or not. ARCH(h) tests whether there is no ARCH up to order h in the residuals.
* Significantly different from zero at the 5% level of significance

In Table 3 we can see the results for the short-term revision and the long-term revision for the G-7 countries made by Faust, Rogers and Wright (2004) and in the last column we have added our results obtained for the Netherlands in case of the SA q-o-q revisions. Our findings for Dutch GDP growth rates allow comparison with Faust *et al.* (2004) because the residuals for the different equations behave well. For the short-term revision the null hypothesis for forecast rationality is rejected for all countries, except for France and the US. The preliminary estimate has a particularly strong effect on revisions in Germany (-0.76), followed by the Netherlands (-0.40). The estimated intercept for the Netherlands (0.34) is of the same order of magnitude as for Germany, Canada, Japan and the UK. For the long-term revision we can still see that the null hypothesis cannot be rejected for France, and for the US it cannot be rejected at the 1% level of significance. For the Netherlands the preliminary estimate has a considerably strong effect on revisions (-0.78) with a very significant t-value. It is followed by Italy (-0.64), the UK (-0.52) and Japan (-0.41). The intercept term is also very high for the Netherlands (0.53), followed by the UK and Canada (0.44). Because of the high $\bar{R}^2$ there is rather overwhelming evidence that GDP growth rates are also predictable for the Netherlands. The forecast rationality hypothesis is violated for the short-term revision and the long-term revision.

Table 3 Our Dutch results compared with the G-7 countries

Short-term revision	Canada	France	Germany	Italy	Japan	UK	US	NL
a	0.29*	0.02	0.31*	0.19*	0.26*	0.27*	0.07	**0.34***
	(3.00)	(0.26)	(2.15)	(2.72)	(4.46)	(4.26)	(1.68)	**(3.66)**
b	-0.30*	0.01	-0.76*	-0.27*	-0.25*	-0.32*	-0.01	**-0.40***
	(-2.97)	(0.07)	(-4.15)	(-2.49)	(-4.94)	(-6.15)	(-0.37)	**(-4.68)**
F	9.50	0.10	18.50	7.90	25.80	43.00	3.90	**10.95**
p -value	0.01	0.94	0.00	0.02	0.00	0.00	0.14	**0.00**
$\bar{R}^2$	0.23	-0.03	0.44	0.20	0.27	0.26	-0.01	**0.31**
Long-term revision								
a	0.44*	0.12	0.28*	0.34*	0.33*	0.44*	0.17	**0.53***
	(4.94)	(1.32)	(2.90)	(4.88)	(4.25)	(6.11)	(2.28)	**(5.78)**
b	-0.39*	-0.24	-0.48*	-0.64*	-0.41*	-0.52*	-0.1	**-0.78***
	(-4.80)	(-1.78)	(-4.29)	(-6.54)	(-7.18)	(-8.55)	(-1.16)	**(-11.25)**
F	26.70	3.30	18.70	49.40	57.40	83.30	7.60	**63.75**
p -value	0.00	0.20	0.00	0.00	0.00	0.00	0.02	**0.00**
$\bar{R}^2$	0.27	0.07	0.40	0.62	0.42	0.52	0.02	**0.61**

Notes: Newey-West HAC consistent covariance t-values are given in parenthesis. The F-statistic and its p-value are used as a test whether the two coefficients are equal to zero. The last column contains our results for the Netherlands (see the SA q-o-q regression results from Table 2). The other columns are the results found by Faust. Rogers and Wright (2004).

We could also extend the simple linear regression model by adding variables to the model, such as a lagged revision, lagged preliminary estimate and a seasonal dummy. This may strengthen our evidence against forecast rationality. It seems reasonable that we distinguish between seasons because the four seasons may have a different effect on the revisions of GDP. As said in the introduction GDP exhibits a regular seasonal pattern reaching a peak in the fourth quarter and then falling in the first quarter of next year. So, for example in our model we want to allow the fourth quarter to behave differently from the first quarter. In theory, it should not matter if we include seasonal dummies to seasonally adjusted series, but when the seasonal dummies are significantly different from zero then it is possible that there are inefficiencies in the seasonal adjustment procedure. It also should not matter to include dummies for the NSA revisions y-o-y, because changes y-o-y should exclude the seasonal variations. To allow for this possibility, we construct three dummy variables: D_1, D_2 and D_3. Thus, we take the fourth quarter of the year as the reference category. D_1 equals 1 in the first quarter and zero otherwise, D_2 and D_3 equal 1 in respectively the second and the third quarter and zero otherwise. If we incorporate the dummy variables next to the lagged revisions and preliminary estimates into our model, our extended model becomes:

$$r_t = a + b\,x_t^p + \sum_{i=1}^{k} g_i\, r_{t-i} + \sum_{j=1}^{l} f_j\, x_{t-j}^p + d_1 D_1 + d_2 D_2 + d_3 D_3 + u_t^* \quad (3.2)$$

where a is a constant. For the first, second and third quarter, the intercept equals $a + d_1$, $a + d_2$ and $a + d_3$ respectively. For the fourth quarter, the intercept is a. For this model we have to test whether all the coefficients are jointly equal to zero, that is $H_0 : a = b = g_1 = \ldots = g_k = f_1 = \ldots = f_l = d_1 = d_2 = d_3 = 0$ (or individually). If the preliminary estimate contains all of the information at the time of publication the additional terms should be insignificantly different from zero. Table 4 displays the extended regression with seasonal dummies, a lagged dependent variable and a lagged preliminary variable.

The next step is to examine the extended forecast efficiency regressions adding the seasonal dummies and a first lag of the revisions and the preliminary estimates into the model (3.2). From Table 4 we can see that the joint hypothesis $d_1 = d_2 = d_3 = 0$ is only rejected for the NSA very short-term revision y-o-y. However we cannot reject at the 1% level of significance. We can reject the hypothesis of forecast rationality if the p-value for the F-statistic of the joint hypothesis $a = b = g_1 = f_1 = d_1 = d_2 = d_3 = 0$ is less than 5%. For all the revisions, except the SA very short-term revision q-o-q, we can reject the null hypothesis and thus the forecast rationality expectation is violated. Compared to the Mincer-Zarnowitz regression the inclusion of the additional variables has increased $\bar{R}^2$ in most cases. We see that adding a lagged revision, a lagged preliminary estimate and seasonal dummies have not changed our previous conclusions considerably. Our findings for the short- and long-term revisions are consistent with the results from the Mincer-Zarnowitz regression, thus it strengthens our evidence that these revisions are biased. For the SA short-term revision q-o-q the result shows that the intercept and the preliminary GDP estimate are of the same order when some variables are added to the model, because the added variables are insignificant. For the SA long-term revision q-o-q we can see that the added lagged revision is significantly different from zero, but the lagged preliminary estimate is insignificant and this has not changed the coefficients considerably. Only the intercept term has decreased from 0.53 to 0.24.

Table 4 Extended Mincer-Zarnowitz regression

	Very short-term revision			Short-term revision			Long-term revision		
	SA q-o-q	SA y-o-y	NSA y-o-y	SA q-o-q	SA y-o-y	NSA y-o-y	SA q-o-q	SA y-o-y	NSA y-o-y
a	0.10	-0.03	-0.04	0.28	0.41	0.25	0.24	0.22	0.28
	(1.42)	(-0.19)	(-1.00)	(1.62)	(1.26)	(1.35)	(1.39)	(0.57)	(1.01)
b	-0.08	-0.12	0.00	-0.38	-0.38	-0.01	-0.77	-0.75	-0.19
	(-1.44)	(-1.80)	(-0.13)	(-4.01)	(-3.85)	(-0.21)	(-10.53)	(-5.18)	(-1.02)
g_1	0.00	0.68	-0.02	-0.12	0.75	0.49	0.16	0.75	0.52
	(-0.01)	(8.23)	(-0.29)	(-0.88)	(8.64)	(3.81)	(1.03)	(4.34)	(4.36)
f_1	-0.03	0.12	0.02	-0.04	0.25	0.00	0.23	0.65	0.15
	(-0.60)	(1.75)	(0.86)	(-0.29)	(3.77)	(-0.04)	(1.99)	(5.64)	(0.87)
d_1	-0.11	-0.04	0.03	-0.07	0.01	-0.08	0.17	0.09	0.12
	(-0.80)	(-0.18)	(0.40)	(-0.41)	(0.05)	(-0.53)	(0.79)	(0.28)	(0.46)
d_2	-0.05	-0.01	0.00	0.21	0.00	-0.17	0.14	0.08	-0.06
	(-1.22)	(-0.16)	(0.27)	(1.26)	(-0.02)	(-0.92)	(0.87)	(0.28)	(-0.28)
d_3	-0.04	0.08	0.10	0.19	0.07	-0.11	0.24	0.19	0.04
	(-0.95)	(0.77)	(3.62)	(1.12)	(0.26)	(-0.59)	(1.48)	(0.56)	(0.15)
BG(1)	0.84	0.17	0.54	0.54	0.36	0.68	0.81	0.58	0.73
BG(4)	0.13	0.00*	0.72	0.38	0.09	0.67	0.43	0.11	0.01*
$\bar{R}^2$	-0.03	0.48	-0.01	0.30	0.49	0.14	0.65	0.46	0.19
F	0.68	15.34*	2.57*	7.56*	16.28*	12.06*	54.34*	9.02*	9.81*
p -val.	0.69	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00
F^*_{seas}	0.83	0.24	4.39*	1.01	0.04	0.30	0.82	0.15	0.16
p^* -val.	0.48	0.87	0.01	0.39	0.99	0.83	0.48	0.93	0.92

Notes: The sample begins in 1986.1 and ends in 2002.4 and the short-term revision ends in 2000.4. Newey-West HAC consistent covariance t-values are given in parentheses. The F-statistic and its p-value are used as a test whether the seven coefficients are equal to zero. The F*(seas)-statistic and its p*-value are used as a test whether the three seasonal dummy variables are equal to zero. BG(h) denotes the Breusch-Godfrey test statistic for up to h-th order autocorrelation and we report the probability value for this diagnostic test.
*Significantly different from zero at the 5% level of significance

To summarise, for the short-term and long-term revision the preliminary estimates are biased and we can only interpret the coefficients for the SA short-term revision q-o-q and the SA long-term revision q-o-q because of the well behaved residuals. In the next section we shall use a more general approach and investigate whether the results confirm the results just obtained.

4 THE STATE-SPACE MODEL

State-space modelling is more and more used in economics[4]. There are several academic studies of the Kalman filter and the state-space model, such as Howrey (1978, 1984) investigating the use of preliminary data in econometric forecasting while the data are subject to revisions. Conrad and Corrado (1979) applied the Kalman filter to improve upon published preliminary estimates of monthly retail sales by using the ARIMA retail sales model. Patterson (1995a, b) also proposed state-space techniques and the Kalman filter to obtain minimum mean square error forecasts and Mariano and Tanizaki (1995) considered this technique for the prediction of US per capita consumption data. The textbook of Harvey (1989) gives an exhaustive presentation of the general characteristics of state-space models and the Kalman filter, and shows how the Kalman filter can be applied to a wide range of models. A state-space representation is made up of a measurement equation, expressing observed variables or signal variables as a function of unobserved or state variables and a transition equation which governs the evolution of the unobservable variables. The Kalman filter is a recursive algorithm which, combined with a maximum likelihood estimation method, can be used to estimate the unobserved variables. In other words, the Kalman filter extracts the unobserved variables from the data via a recursive algorithm. This approach is often used when we are dealing with an unobserved variable, for example the equilibrium level of output or potential output, and the equilibrium level of unemployment or NAIRU. In this section we want to forecast the revisions of the data by using the state-space method. We consider our final data as an unobserved variable. In sub-section 4.1 we introduce the state-space representation, following the framework of Harvey (1989). Sub-section 4.2 applies the model to the GDP revisions and in sub-section 4.3 we present our state-space results.

4.1 **The standard state-space representation**

We follow the notation of Harvey (1989, pp. 100-106) to introduce the standard state-space representation. We have the measurement equation

$$y_t = Z_t a_t + d_t + e_t, \quad t = 1, \ldots, T \qquad (4.1.1)$$

where Z_t is an $N \times m$ matrix which includes unknown parameters; a_t is an unobserved $m \times 1$ vector and is also known as the state vector; y_t, d_t and e_t are $N \times 1$ vectors. y_t and d_t are vectors

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[4] In the beginning state-space models were mostly used in engineering applications, for example to predict the position of a satellite in the next period.

observed at time t and e_t is a stochastic vector with mean zero and covariance matrix H_t. The matrix Z_t selects the variables or linear combinations of the variables in a_t for which current observations are available. The time-varying coefficients a_t are determined by the transition equation

$$a_t = T_t a_{t-1} + c_t + R_t h_t, \quad t = 1, \ldots, T \tag{4.1.2}$$

where T_t is an $m \times m$ matrix which also includes unknown parameters, c_t is an $m \times 1$ vector, R_t is an $m \times g$ matrix and h_t is an $g \times 1$ random vector with mean zero and covariance matrix Q_t.

We use the vectors d_t and c_t to include known effects or patterns into the model. In the absence of these effects the vectors are equal to zero. Furthermore we make the following assumptions on the initial state. First of all, the initial vector a_0 has a mean of a_0 and a covariance matrix P_0. Thus

$$E(a_0) = a_0 \quad \text{and} \quad Var(a_0) = P_0 \tag{4.1.3}$$

Secondly, the disturbances e_t and h_s are mutually uncorrelated in all time periods and uncorrelated with the initia l state, that is

$$E(e_t h_s') = 0, \quad \forall s, t = 1, \ldots, T \tag{4.1.4}$$

and

$$E(e_t a_0') = 0, \quad E(h_t a_0') = 0 \quad \text{for } t = 1, \ldots, T \tag{4.1.5}$$

Now, we want to derive the Kalman filter and show its use in forecasting. The filter is an efficient algorithm to compute the optimal estimator a_t of a_t, based on the information up to (and including) t. The covariance matrix P_t of estimation errors is equal to

$$P_t = E\left[(a_t - a_t)(a_t - a_t)' \right] \tag{4.1.6}$$

Let us assume that a_{t-1} and P_{t-1} are known, then we can define the following prediction equations:

$$a_{t|t-1} = T_t a_{t-1} + c_t \tag{4.1.7}$$

and

$$P_{t|t-1} = T_t P_{t-1} T_t' + R_t Q_t R_t' \tag{4.1.8}$$

The corresponding prediction of y_t and the prediction error n_t are

$$\hat{y}_{t|t-1} = Z_t a_{t|t-1} + d_t \tag{4.1.9}$$

$$n_t = y_t - \hat{y}_{t|t-1} = Z_t a_t + d_t + e_t - Z_t a_{t|t-1} - d_t = Z_t \left(a_t - a_{t|t-1}\right) + e_t \tag{4.1.10}$$

The variance F_t of the prediction error $n_t = y_t - \hat{y}_{t|t-1}$ is

$$F_t = Z_t P_{t|t-1} Z_t' + H_t \tag{4.1.11}$$

Thus, the filtered estimate of a_t is equal to a_t and is updated from $a_{t|t-1}$ since y_t is known, and the updated equation for a_t becomes:

$$\begin{aligned} a_t &= a_{t|t-1} + E\left[\left(a_t - a_{t|t-1}\right)\left(y_t - \hat{y}_{t|t-1}\right)'\right] \cdot E\left[\left(y_t - \hat{y}_{t|t-1}\right)\left(y_t - \hat{y}_{t|t-1}\right)'\right]^{-1} \cdot \left(y_t - \hat{y}_{t|t-1}\right) = \\ & a_{t|t-1} + P_{t|t-1} Z_t' F_t^{-1} \left(y_t - Z_t a_{t|t-1} - d_t\right) \end{aligned} \tag{4.1.12}$$

where

$$\begin{aligned} & E\left[\left(a_t - a_{t|t-1}\right)\left(y_t - \hat{y}_{t|t-1}\right)'\right] = E\left[\left(a_t - a_{t|t-1}\right)\left(Z_t \left(a_t - a_{t|t-1}\right) + e_t\right)'\right] = \\ & E\left[\left(a_t - a_{t|t-1}\right)\left(a_t - a_{t|t-1}\right)' Z_t'\right] = P_{t|t-1} Z_t' \end{aligned} \tag{4.1.13}$$

and

$$E\left[e_t\left(a_t - a_{t|t-1}\right)'\right] = 0 \tag{4.1.14}$$

The updated equation (4.1.12) shows how the new information, y_t, is used to modify the previous prediction of a_t. As we can see from the equation (4.1.12) some fraction $P_{t|t-1}Z_t'F_t^{-1}$ of the difference between y_t and its predicted value, $\hat{y}_{t|t-1} = Z_t a_{t|t-1} + d_t$, is added to the previous prediction of a_t.

The updated covariance matrix P_t is equal to

$$\begin{aligned} &P_t \equiv E\left[(a_t - a_t)(a_t - a_t)'\right] = E\left[\left(a_t - a_{t|t-1}\right)\left(a_t - a_{t|t-1}\right)'\right] - \\ &E\left[\left(a_t - a_{t|t-1}\right)\left(y_t - \hat{y}_{t|t-1}\right)'\right] \cdot E\left[\left(y_t - \hat{y}_{t|t-1}\right)\left(y_t - \hat{y}_{t|t-1}\right)'\right]^{-1} \cdot \\ &E\left[\left(y_t - \hat{y}_{t|t-1}\right)\left(a_t - a_{t|t-1}\right)'\right] = P_{t|t-1} - P_{t|t-1}Z_t'F_t^{-1}Z_t P_{t|t-1} \end{aligned} \tag{4.1.15}$$

The distribution of y_t conditional on (a_t, I_{t-1}), where $I_{t-1} = \left(y_{t-1}', y_{t-2}', \ldots, y_1', a_{t-1}', a_{t-2}', \ldots, a_1'\right)$, is given by the following: $y_t | a_t, I_{t-1} \sim N\left(\hat{y}_{t|t-1}, F\right)$. Consequently, the probability density function can be represented as[5]:

$$f_{Y_t|A_t, I_{t-1}}\left(y_t | a_t, I_{t-1}\right) = (2p)^{-n/2} |F|^{-1/2} \exp\left\{-\frac{1}{2}\left(y_t - \hat{y}_{t|t-1}\right)' F^{-1}\left(y_t - \hat{y}_{t|t-1}\right)\right\} \tag{4.1.16}$$

Finally, the likelihood function and the log-likelihood are equal to respectively

$$L(q) = \prod_{t=1}^{T} (2p)^{-n/2} \cdot |F|^{-1/2} \exp\left\{-\frac{1}{2}\left(y_t - Z_t a_{t|t-1} - d_t\right)' F^{-1}\left(y_t - Z_t a_{t|t-1} - d_t\right)\right\} \tag{4.1.17}$$

[5] For more details see also Hamilton (1994).

$$\Rightarrow \ln L(q) = -\frac{nT}{2}\ln(2p) - \frac{1}{2}\sum_{i=1}^{T}\ln|F_i| - \frac{1}{2}\sum_{i=1}^{T} n_i' F_i^{-1} n_i \qquad (4.1.18)$$

4.2 The state-space model applied to GDP revisions

Mariano and Tanizaki (1995) characterise the relationship between final data and preliminary data while taking into account the errors in the preliminary data. Let X_t^f and X_t^p be the unobserved and the observed vector respectively. Following Mariano and Tanizaki (1995), we have the following two equations:

Measurement equation $\qquad q_t(X_t^p, X_t^f; g) = e_t \qquad$ (4.2.1)

Transition equation $\qquad f_t(X_t^f, X_{t-1}^f; q) = h_t \qquad$ (4.2.2)

$$\begin{pmatrix} e_t \\ h_t \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} H_t & 0 \\ 0 & Q_t \end{pmatrix}\right) \quad \text{for } t = 1, 2, \ldots, T$$

where g, q are unknown parameters to be estimated, q_t and f_t are assumed to be known. This state-space model is written in the Gaussian state-space form.

In our approach, we consider the case where equations (4.2.1) and (4.2.2) are linear and where e_t and h_t are normally distributed. Under these assumptions, equation (4.2.1) and (4.2.2) are written as:

Measurement equation $\qquad X_t^p = Z_t X_t^f + d_t + e_t \qquad$ (4.2.3)

Transition equation $\qquad X_t^f = T_t X_{t-1}^f + c_t + R_t h_t \qquad$ (4.2.4)

$$\begin{pmatrix} e_t \\ R_t h_t \end{pmatrix} \sim \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} H_t & 0 \\ 0 & R_t R_t' \end{pmatrix}\right)$$

The state vector X_t^f contains unobserved stochastic processes and unknown fixed effects. The transition equation, or state equation, is generated by a Markov process. The measurement equation shows that the observation vector X_t^p is related to the state vector X_t^f and the vector of disturbances e_t. If the matrices Z_t, T_t and R_t are constant over time (time-invariant) then we can skip the time indices and the matrices Z, T and R remain.

Suppose we wish to compare our state-space model with our econometric model, then we also have to construct a very short-term, a short-term and a long-term revision period. Therefore, for the very short-term revision we suppose that at time t two data series are available, that is the preliminary estimate x_t^p and the lagged revised estimate x_{t-1}^{t+1} so that we can define the observed vector $X_t^p = \left[x_t^p, x_{t-1}^{t+1}\right]'$. So, the measurement equation describes two relationships. The first describes the relationship between the preliminary estimate and the final data. And the second relationship states that the first lag of the first revision, x_{t-1}^{t+1}, is identically equal to the first lag of the final data, x_{t-1}^f. For the short-term revision the second relationship states that the first lag of the eighth revision, x_{t-1}^{t+8}, is identically equal to the first lag of the final data. For the long-term revision the first lag of the final data is just equal to the first lag of the final data, so this is just an identity. Hence, for the short-term and long-term revision the observed vector X_t^p is equal to $\left[x_t^p, x_{t-1}^{t+8}\right]'$ and $\left[x_t^p, x_{t-1}^f\right]'$ respectively. Moreover, in the state vector we include s_t, s_{t-1} and s_{t-2} representing the seasonal pattern of vector x_t^p. Hence, for the very short-term revision the measurement- and transition equation are written as:

Measurement equation
$$\begin{bmatrix} x_t^p \\ x_{t-1}^{t+1} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_t^f \\ x_{t-1}^f \\ s_t \\ s_{t-1} \\ s_{t-2} \end{bmatrix} + \begin{bmatrix} e_t \\ 0 \end{bmatrix} \tag{4.2.5}$$

Transition equation
$$\begin{bmatrix} x_t^f \\ x_{t-1}^f \\ s_t \\ s_{t-1} \\ s_{t-2} \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & -1 & -1 & -1 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} x_{t-1}^f \\ x_{t-2}^f \\ s_{t-1} \\ s_{t-2} \\ s_{t-3} \end{bmatrix} + \begin{bmatrix} h_t \\ 0 \\ w_t \\ 0 \\ 0 \end{bmatrix} \tag{4.2.6}$$

The Kalman filter is used to obtain optimal forecasts and this is a recursive algorithm for sequentially updating the mean and the variance of the unknown state vector. The Kalman filter for our model is given by the following recursions:

$$n_t = \left(x_t^p - \hat{x}_t^p\right) = Z x_t^f + e_t - Z\hat{x}_t^f = Z\left(x_t^f - \hat{x}_t^f\right) + e_t \tag{4.2.7}$$

$$F_t = Z P_t Z' + H_t \tag{4.2.8}$$

$$\hat{x}_t^f = \hat{x}_{t|t-1}^f + P_{t|t-1} Z' F_t^{-1}\left(x_t^p - Z\hat{x}_{t|t-1}^f\right) \tag{4.2.9}$$

$$P_t = P_{t|t-1} - P_{t|t-1} Z' F_t^{-1} Z P_{t|t-1} \tag{4.2.10}$$

where $\hat{x}_1^f = \hat{x}^f$, $P_1 = P$, n_t is the prediction error, with zero mean and the variance is equal to F_t .

4.3 **State-space results**

We start the Kalman filter by setting $\hat{x}_0^f = [0,0,0,0,0]'$ and $P_0 = l\, I_5$ where l is an arbitrary small number. Even arbitrary large numbers for both $\hat{x}_0^f$ and P_0 do not change the obtained estimates for a_{11}, a_{12}, b_{11}, b_{12}, s_e^2, s_h^2 and s_w^2. After achieving convergence we get asymptotically efficient estimates of the parameters in the state-space model[6]. The resulting estimates of the estimated maximum likelihood parameters for the three different revision periods are reported in Table 5. For each estimated parameter we report its t-statistic in parenthesis to test whether the parameter is significantly different from zero. We can see that the estimates a_{11} are always significantly different from zero, except the SA long-term revision y-o-y. The estimate of $a_{11} + a_{12}$ are almost all positive and smaller than one. This strengthens our previous conclusion that there is a tendency for pessimism in Dutch GDP announcements. The extent to which the unobserved variables evolve over time depends on the three variance parameters s_e^2, s_h^2 and s_w^2 which are also estimated by the maximum likelihood method. A rule of thumb is that the higher the ratio of the variance of the transition equation residuals to the measurement equation residuals, that is the signal-to-noise ratio s_h^2 / s_e^2, the more explanatory power is given to the unobserved vector, X_t^f, and this leads to a better fit of the measurement equation (Boone, 2000). Furthermore, the higher the variance of the seasonal component, s_w^2, relative to the variance of the measurement equation, s_e^2, the greater the importance of seasonal influences for variability in X_t^p. For the three different series the signal-to-noise ratios

[6] The model is estimated by a Gauss program and is partly written by Paul Söderlind and Peter Vlaar.

decrease the longer the revision period. As can be seen from Table 5 the zero estimate of s_w^2 for the three series and revision periods implies that the seasonal component s_t does not change over time and indicates that the slope of the seasonal component can be regarded as constant. Indeed, this is actually the case because in the measurement equation (4.2.5) we set the slope coefficient of s_t fixed at one. The estimated series $\hat{x}_t^f$ are plotted in Figure 4 for the three different series and revision periods, along with the actual data. The predicted data of applying the state-space estimation procedure have a similar pattern as the actual data and they are very close to each other, so this gives us a strong indication that we can predict the final data x_t^f. For the long-term revision the two series differ the most and this can be due to the low signal-to-noise ratio.

In Figure 5 the prediction errors are displayed for the three different series and revision periods. To compare the state-space results among the three revision periods we introduce two variables measuring the mean squared error (MSE) and the mean absolute error (MAE). The MSE and the MAE can be expressed as follows

$$MSE := \frac{1}{T}\sum_{t=T_0}^{T_0+T}\left(x_t^f - \hat{x}_t^f\right)^2 \qquad (4.3.1)$$

$$MAE := \frac{1}{T}\sum_{t=T_0}^{T_0+T}\left|x_t^f - \hat{x}_t^f\right| \qquad (4.3.2)$$

with $(T_0, T_0 + T)$ the prediction period with 55 observations for the short-term revision and 63 observations for the very short-term revision and the long-term revision. The results for the MSE and the MAE are given in Tables 6 and 7, respectively. These tables clearly show that the errors increase if the horizon extends from one to eight quarters and remain relatively stable if the horizon is extended further. These results from the state-space model seem to imply that the Dutch GDP-statistic after eight subsequent releases could be considered as definitive, or final. Given the notion that revisions tend to be pro-cyclical, two years is probably the time needed to assess with hindsight the correct stage of the business cycle.

The Kalman-filter set-up provides a framework to analyze the number of releases needed for quarterly revisions to fade away. For instance, instead of considering a revision over eight quarters, the framework naturally allows to consider eight quarterly revisions separately. In this study, however, the state-space approach serves as a robustness-check for the Mincer-Zarnowitz regressions. To compare our state-space results with the Mincer-Zarnowitz results we have to test the hypothesis of forecast rationality discussed in the paper from Mankiw, Runkle and Shapiro (1984). They considered a regression model for testing the rationality of preliminary estimates. The regression model can be written, using our notation, as follows:

$$x_t^p = a + b\, x_t^f + e_t \qquad (4.3.3)$$

where the error term e_t is assumed to be uncorrelated with the final data x_t^f. Under the hypothesis of forecast rationality, the preliminary estimates are equal to the final estimates and this boils down to testing $H_0 : a = 0,\ b = 1$[7].

Our measurement equation can be written in the following form:

$$x_t^p = a_{11}\, x_t^f + a_{12}\, x_{t-1}^f + e_t \qquad (4.3.4)$$

If we compare this model with equation (4.3.3) then we can test $H_0 : a_{11} + a_{12} = 1$. The Wald-statistic for testing whether the sum of a_{11} and a_{12} is equal to 1 is shown at the bottom of Table 5. For all the series we can reject the null hypothesis and this means that the preliminary estimates are biased. The state space results are therefore even stronger than the Mincer-Zarnowitz results, in which the null hypothesis for forecast rationality is only not rejected for the SA very short-term revision q-o-q.

[7] The null hypothesis can also be derived from equation (3.1):
$r_t = (x_t^f - x_t^p) = a + b\, x_t^p + u_t \Leftrightarrow x_t^f = a + (b+1) x_t^p + u_t \Leftrightarrow x_t^p = a^* + b^* x_t^f + u_t^*$
where $a^* = -a/(b+1)$, $b^* = 1/(b+1)$ and $u_t^* = -u_t/(b+1)$. Hence, $H_0 : a = b = 0$ corresponds to $H_0 : a^* = 0,\ b^* = 1$.

Table 5 State-space results

	Very short-term revision			Short-term revision			Long-term revision		
	SA q-o-q	SA y-o-y	NSA y-o-y	SA q-o-q	SA y-o-y	NSA y-o-y	SA q-o-q	SA y-o-y	NSA y-o-y
a_{11}	0.93	0.91	0.94	0.78	0.58	0.74	0.40	0.20	0.60
	(21.37)	(10.57)	(36.73)	(8.27)	(4.08)	(12.51)	(2.38)	(0.95)	(8.68)
a_{12}	0.06	0.09	0.04	0.11	0.25	0.16	0.46	0.62	0.24
	(1.28)	(1.14)	(1.62)	(0.87)	(1.83)	(2.74)	(2.75)	(3.09)	(3.23)
b_{11}	0.23	0.69	0.76	0.36	0.73	0.81	0.41	1.00	0.99
	(1.58)	(4.89)	(5.75)	(2.67)	(4.98)	(5.75)	(2.94)	(6.53)	(6.95)
b_{12}	0.20	0.25	0.19	0.38	0.25	0.14	0.45	-0.03	-0.04
	(1.67)	(1.90)	(1.59)	(3.45)	(1.79)	(1.11)	(3.57)	(-0.17)	(-0.32)
s_e^2	0.30	0.65	0.16	0.57	0.82	0.42	0.64	0.77	0.49
	(5.82)	(9.53)	(8.38)	(11.40)	(9.21)	(9.65)	(10.07)	(10.18)	(9.85)
s_h^2	0.88	0.92	0.85	0.74	0.86	1.03	0.47	0.65	0.98
	(8.99)	(7.95)	(11.04)	(7.96)	(10.05)	(11.53)	(8.03)	(8.11)	(10.06)
s_w^2	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00
Wald	259*	701*	17858*	115*	500*	2336*	56*	623*	1470*
N	24	27	25	20	26	26	18	28	26

Note. The second last row contains the values for the Wald-test whether the coefficient $a_{11} + a_{12}$ is equal to 1. N stands for the number of iterations. * Significantly different from zero at the 5% level of significance

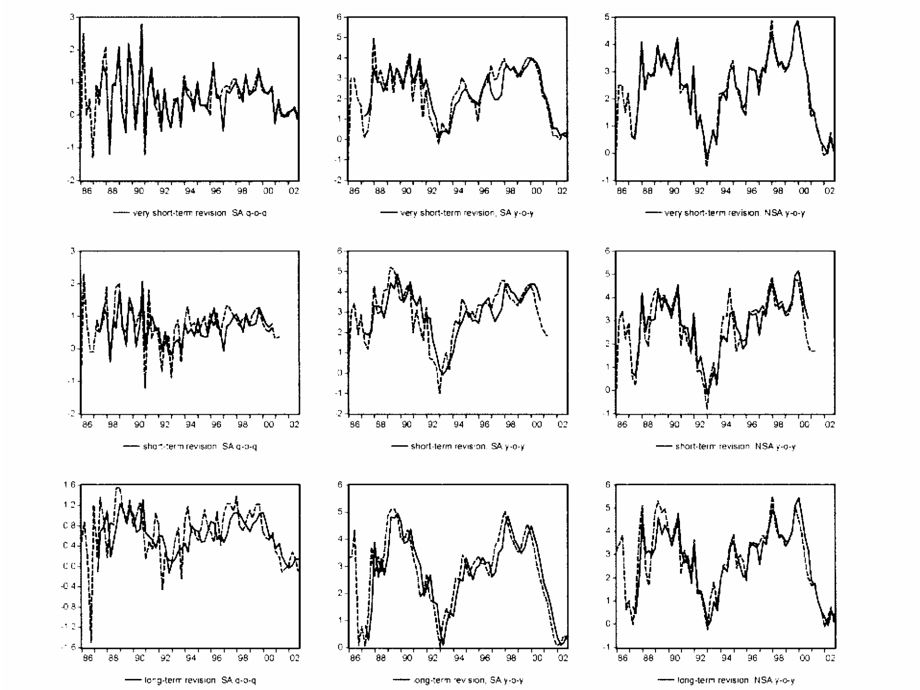
Table 6: Mean square errors

	Very short-term revision	Short-term revision	Long-term revision
SA q-o-q	0.08	0.22	0.15
SA y-o-y	0.34	0.51	0.41
NSA y-o-y	0.03	0.24	0.35

Table 7: Mean absolute errors

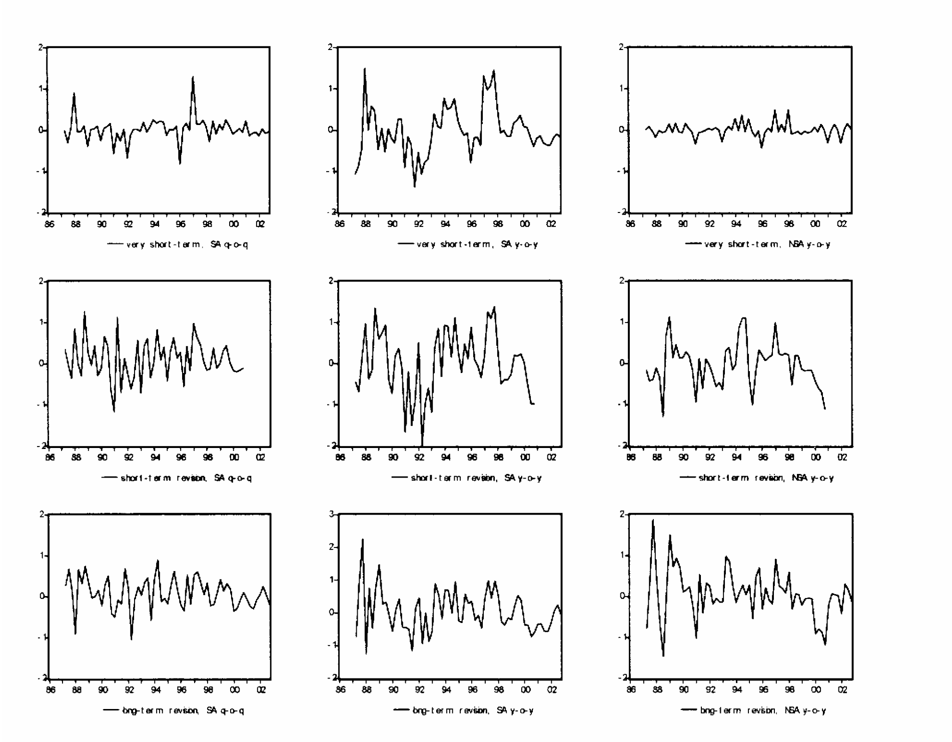
	Very short-term revision	Short-term revision	Long-term revision
SA q-o-q	0.17	0.34	0.31
SA y-o-y	0.44	0.54	0.51
NSA y-o-y	0.11	0.36	0.43

Figure 4 The estimated series $\hat{x}_t^f$ along with our actual data x_t^f



Explanation: (-----), actual data; (—) predicted data of applying the state-space estimation procedure.

Figure 5 The errors between the actual data x_t^f and the predicted data $\hat{x}_t^f$



The graphs indicate that the errors fluctuate around the mean zero. The SA very short-term revision q-o-q and the NSA very short-term revision y-o-y have the smallest errors among the different graphs.

5 CONCLUSIONS

This paper investigates whether Dutch GDP revisions are predictable. The research is based on an article written by Faust, Rogers and Wright (2004) that studied the GDP revisions for the G-7 countries and showed some evidence of predictability of revisions for the UK, Italy and Japan. The authors characterise the revision process by two polar characterisations (see Mankiw and Shapiro, 1986), i.e. the news and the noise characterisation. Under the news characterisation the preliminary estimates are based on all available information, thus the revisions reflect news. Contrary to the news characterisation, preliminary estimates are measured with error in the noise characterisation and these estimates can be useful to predict forthcoming revisions. Forecast rationality tests are applied to distinguish between these two characterisations. The three countries are found to be characterised by the noise characterisation, because the revisions reflect news that is already available at the time of publication. We examined the Dutch GDP releases by using the same technique.

The Dutch quarterly GDP growth rates are gathered from Statistics Netherlands (CBS) publications and run from 1986 up to 2002. The available published data by CBS are the seasonally adjusted (SA) GDP growth rates, defined as the quarter-over-quarter (q-o-q) percentage change, and the non-seasonally adjusted (NSA) GDP growth rates, defined as the year-over-year (y-o-y) percentage change. Moreover, we constructed the SA GDP growth rates y-o-y to examine a possible relationship with the NSA GDP growth rates y-o-y.

We investigated three kinds of revisions, viz. the very short-term revision, short-term revision and the long-term revision. The first published figures for GDP growth rates are considered as preliminary data. The very short-term revision is the revision between the preliminary estimate and the revised estimate after one quarter. The short-term revision is defined as the revision between the preliminary estimate and the revised estimate after a period of eight quarters. The long-term revision is the revision between the preliminary estimate and the final figure, in our case the one published at 2002Q4.

Results emerging from our analyses are the following. Firstly, from the summary statistics it follows that the revisions are large for the short-term revision and the long-term revision. They are positive on average implying that there is a downward bias in the preliminary estimates. So, there is a tendency for pessimism in Dutch GDP announcements. In contrast to the article from Faust *et al.* (2004) we did not report a t-value for testing whether the mean revision is equal to zero because the revisions are not independent and hence the t-value is an invalid statistic.
Secondly, we studied the revisions based on the article of Faust, Rogers and Wright (2004) by using an ordinary least squares regression model, in our study called the Mincer-Zarnowitz regression. This econometric model expresses revisions as a function of preliminary estimates plus a constant term. We

test the ‘noise characterisation’ by checking whether the constant term and the coefficient of the preliminary estimates are significantly different from zero, i.e. whether the revisions are biased. The results indicate evidence for the predictability of the SA short-term revision q-o-q and the SA long-term revision q-o-q. For these two series the Mincer-Zarnowitz test is valid, because the errors seem a white noise process. For the SA short- and long-term revision q-o-q the coefficient estimates suggest that an increase in the preliminary GDP growth rate by one percentage point leads to a decrease in the revision by 0.40 and 0.78 percentage point, respectively. Also a more general specification of the model by adding explanatory variables to the Mincer-Zarnowitz regression model, leads to the same conclusion, namely that the SA short- and long-term revision q-o-q are predictable. The SA short- and long-term revision are compared with the results for the G-7 countries made by Faust, Rogers and Wright (2004) because they only discuss these two revisions. For the short-term revision our findings are approximately of the same order as for Italy, Japan and the UK. For the long-term revision the Dutch preliminary estimates have the strongest effect on revisions compared to the G-7 countries with a very significant t-value.

Thirdly, we used the more general state-space method to study the revisions. These results confirm also that the short-term and long-term revisions are biased, so that there is evidence for predictability. This strengthens our obtained evidence from the Mincer-Zarnowitz regression.

To summarise, for the SA short-term revision q-o-q and the SA long-term revision q-o-q we find evidence of predictability of the revisions. This implies that, at least regarding the sample under consideration, the preliminary estimates contain useful information about future revisions. For future research it may be worthwhile to examine the different components of GDP, such as consumption, investment, government purchases, exports and imports by using the Mincer-Zarnowitz regression. This may provide useful information about which component causes the main errors in the preliminary estimates. Moreover, the Kalman-filter set-up could be extended in order to analyze the number of releases needed for quarterly revisions to fade away

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APPENDIX A DATA OVERVIEW

Table I SA GDP growth rates q-o-q

	1985.1	1985.2	1985.3	1985.4	1986.1	1986.2	1986.3	1986.4	1987.1	1987.2	1987.3
x_t^p	2	-1.5	2	1.5	-1.5	2.5	0	0.5	-0.5	0.9	0.7
x_t^{t+1}	2	-1.5	0	1.5	-1	2.5	0	0.5	-1.3	0.9	0.3
x_t^{t+8}	1.5	-0.6	0.4	1.4	-1.1	2.3	0.8	-0.1	-0.1	0.9	0.5
x_t^f	1.29	0.85	-0.74	2.71	0.49	0.86	0.23	-1.51	1.20	0.17	1.36

	1987.4	1988.1	1988.2	1988.3	1988.4	1989.1	1989.2	1989.3	1989.4	1990.1	1990.2
x_t^p	1.6	1.3	-1.2	0.9	1	2.2	0.1	-0.6	2.2	1.5	-0.5
x_t^{t+1}	1.6	2.1	-1.2	0.9	1	1.7	0.1	-0.5	2.2	1.1	-0.4
x_t^{t+8}	0.9	1.9	-0.4	0.6	1.9	2	0.6	0.5	1.3	1.1	0.7
x_t^f	0.91	0.17	0.86	0.82	1.54	1.55	1.08	0.84	1.29	0.79	0.95

	1990.3	1990.4	1991.1	1991.2	1991.3	1991.4	1992.1	1992.2	1992.3	1992.4	1993.1
x_t^p	0.6	2.8	-0.6	0.8	1.6	0.3	0.8	-0.4	0.8	-0.1	-0.4
x_t^{t+1}	0.7	2.8	-1.2	0.8	1.2	0.3	0.1	-0.5	0.8	-0.1	-0.4
x_t^{t+8}	1.1	1.4	-1.2	1.8	0.3	0.7	0.4	-0.7	0.2	0.4	-0.9
x_t^f	1.24	0.89	0.15	0.49	0.34	1.05	0.81	-0.47	0.28	0.11	0.10

	1993.2	1993.3	1993.4	1994.1	1994.2	1994.3	1994.4	1995.1	1995.2	1995.3	1995.4
x_t^p	0.3	0.6	-0.4	1	0.7	0.5	0.1	1.1	0.3	0.3	0.2
x_t^{t+1}	0.5	0.5	-0.3	1.2	0.8	0.7	0.3	0.9	0.3	0.3	0.3
x_t^{t+8}	0.6	0.9	-0.4	0.8	1.3	0.7	0.8	0.5	0.7	1	0.5
x_t^f	0.48	0.76	-0.24	0.85	1.18	0.67	0.66	0.51	0.75	1.11	0.80

	1996.1	1996.2	1996.3	1996.4	1997.1	1997.2	1997.3	1997.4	1998.1	1998.2	1998.3
x_t^p	0.9	1.6	0.6	0.5	-0.5	0.8	0.7	0.9	1.1	0.83	0.40
x_t^{t+1}	0	1.6	0.7	0.5	0.8	0.9	0.8	1.1	1.10	0.51	0.62
x_t^{t+8}	1.1	0.7	1.1	0.4	0.91	1.33	1.23	1.03	0.90	0.71	0.90
x_t^f	0.66	0.48	1.07	0.42	1.00	1.23	1.23	1.09	1.38	0.80	0.69

	1998.4	1999.1	1999.2	1999.3	1999.4	2000.1	2000.2	2000.3	2000.4	2001.1	2001.2
x_t^p	1.31	0.67	0.71	0.82	1.42	0.95	0.70	0.68	0.93	-0.28	0.48
x_t^{t+1}	1.15	0.75	0.70	1.02	1.44	0.77	0.65	0.69	0.83	-0.06	0.34

Table I *Continued*

	1998.4	1999.1	1999.2	1999.3	1999.4	2000.1	2000.2	2000.3	2000.4	2001.1	2001.2
x_t^{t+8}	0.97	0.71	1.03	1.22	1.27	0.81	0.59	0.51	0.66		
x_t^f	0.88	1.10	0.95	1.22	1.21	0.69	0.56	0.51	0.66	0.29	0.20

	2001.3	2001.4	2002.1	2002.2	2002.3	2002.4
x_t^p	0.05	-0.04	0.11	0.12	0.26	-0.10
x_t^{t+1}	-0.03	-0.07	-0.04	0.15	0.17	-0.13
x_t^{t+8}						
x_t^f	-0.11	-0.03	0.02	0.27	0.17	-0.10

Table II SA GDP growth rates y-o-y

	1985.1	1985.2	1985.3	1985.4	1986.1	1986.2	1986.3	1986.4	1987.1	1987.2	1987.3
x_t^p	NA	NA	NA	4.02	0.45	4.53	2.48	1.47	2.50	0.90	1.60
x_t^{t+1}	NA	NA	NA	1.98	-1.02	3.00	3.00	1.98	1.67	0.09	0.39
x_t^{t+8}	NA	NA	NA	2.71	0.08	3.00	3.41	1.88	2.91	1.50	1.20
x_t^f	2.97	3.52	1.69	4.13	3.32	3.34	4.35	0.06	0.76	0.07	1.20

	1987.4	1988.1	1988.2	1988.3	1988.4	1989.1	1989.2	1989.3	1989.4	1990.1	1990.2
x_t^p	2.72	4.57	2.40	2.60	2.00	2.90	4.26	2.71	3.93	3.21	2.60
x_t^{t+1}	1.49	4.98	2.80	3.41	2.80	2.40	3.75	2.31	3.52	2.91	2.40
x_t^{t+8}	2.21	4.26	2.92	3.02	4.04	4.14	5.19	5.08	4.47	3.54	3.65
x_t^f	3.69	2.64	3.34	2.79	3.42	4.84	5.08	5.10	4.85	4.06	3.93

	1990.3	1990.4	1991.1	1991.2	1991.3	1991.4	1992.1	1992.2	1992.3	1992.4	1993.1
x_t^p	3.83	4.44	2.28	3.62	4.65	2.10	3.54	2.31	1.50	1.10	-0.10
x_t^{t+1}	3.63	4.24	1.87	3.10	3.61	1.09	2.42	1.10	0.70	0.30	-0.21
x_t^{t+8}	4.27	4.37	1.99	3.11	2.29	1.59	3.23	0.70	0.60	0.30	-1.00
x_t^f	4.34	3.93	3.26	2.79	1.88	2.04	2.71	1.73	1.68	0.73	0.02

	1993.2	1993.3	1993.4	1994.1	1994.2	1994.3	1994.4	1995.1	1995.2	1995.3	1995.4
x_t^p	0.60	0.40	0.10	1.50	1.91	1.81	2.32	2.42	2.01	1.81	1.91
x_t^{t+1}	0.80	0.50	0.30	1.91	2.21	2.42	3.03	2.73	2.22	1.81	1.81

Table II *Continued*

	1993.2	1993.3	1993.4	1994.1	1994.2	1994.3	1994.4	1995.1	1995.2	1995.3	1995.4
x_t^{t+8}	0.29	0.99	0.19	1.91	2.62	2.41	3.65	3.34	2.73	3.03	2.73
x_t^f	0.98	1.46	1.10	1.86	2.57	2.48	3.41	3.06	2.61	3.06	3.21

	1996.1	1996.2	1996.3	1996.4	1997.1	1997.2	1997.3	1997.4	1998.1	1998.2	1998.3
x_t^p	1.71	3.03	3.34	3.65	2.21	1.40	1.50	1.91	3.55	3.58	3.27
x_t^{t+1}	0.90	2.21	2.62	2.82	3.65	2.93	3.03	3.65	3.96	3.55	3.37
x_t^{t+8}	3.34	3.34	3.44	3.34	3.14	3.79	3.92	4.57	4.56	3.92	3.59
x_t^f	3.36	3.09	3.05	2.66	3.00	3.77	3.93	4.63	5.02	4.57	4.02

	1998.4	1999.1	1999.2	1999.3	1999.4	2000.1	2000.2	2000.3	2000.4	2001.1	2001.2
x_t^p	3.69	3.24	3.12	3.55	3.67	3.96	3.95	3.80	3.29	2.04	1.81
x_t^{t+1}	3.42	3.06	3.25	3.66	3.96	3.98	3.94	3.59	2.97	2.13	1.81
x_t^{t+8}	3.53	3.33	3.66	3.98	4.29	4.39	3.94	3.21	2.59		
x_t^f	3.81	3.52	3.68	4.22	4.55	4.13	3.72	3.00	2.44	2.03	1.66

	2001.3	2001.4	2002.1	2002.2	2002.3	2002.4
x_t^p	1.17	0.20	0.59	0.23	0.45	0.39
x_t^{t+1}	1.08	0.17	0.19	0.00	0.20	0.14
x_t^{t+8}						
x_t^f	1.03	0.34	0.07	0.14	0.42	0.36

Table III NSA GDP growth rates y-o-y

	1985.1	1985.2	1985.3	1985.4	1986.1	1986.2	1986.3	1986.4	1987.1	1987.2	1987.3
x_t^p	1	0.5	1.5	2.50	-1.00	2.50	2.50	1.50	2.50	0.60	0.50
x_t^{t+1}	1	0.5	1.5	2.50	-0.50	2.50	2.50	1.50	2.20	0.60	0.60
x_t^{t+8}	2	1.9	1.9	3.20	0.10	3.00	3.40	2.20	2.90	0.60	0.20
x_t^f	1.57	4.34	1.98	4.31	3.17	3.47	3.81	0.63	1.02	-0.03	0.82

	1987.4	1988.1	1988.2	1988.3	1988.4	1989.1	1989.2	1989.3	1989.4	1990.1	1990.2
x_t^p	1.90	4.00	2.30	2.90	2.80	2.80	3.90	3.10	3.60	3.20	2.80

	1987.4	1988.1	1988.2	1988.3	1988.4	1989.1	1989.2	1989.3	1989.4	1990.1	1990.2
x_t^{t+1}	1.90	3.90	2.30	2.90	2.80	3.00	3.90	3.30	3.60	3.20	3.00
x_t^{t+8}	1.60	4.10	2.20	1.90	3.70	4.20	4.40	3.90	4.10	3.70	3.40
x_t^f	3.88	5.10	2.38	1.69	3.11	4.77	5.31	4.80	4.97	4.03	3.51

	1990.3	1990.4	1991.1	1991.2	1991.3	1991.4	1992.1	1992.2	1992.3	1992.4	1993.1
x_t^p	3.50	4.20	2.50	2.40	2.50	1.40	3.10	0.90	1.30	0.60	-0.20
x_t^{t+1}	3.60	4.20	2.20	2.40	2.50	1.40	3.20	0.90	1.40	0.60	-0.50
x_t^{t+8}	4.00	4.40	1.90	2.80	2.10	1.70	3.30	0.80	0.90	0.20	-0.80
x_t^f	4.20	4.52	2.15	3.18	2.54	2.08	3.63	1.27	1.37	0.66	-0.23

	1993.2	1993.3	1993.4	1994.1	1994.2	1994.3	1994.4	1995.1	1995.2	1995.3	1995.4
x_t^p	0.20	0.80	0.30	1.90	2.20	1.90	3.00	3.10	2.40	2.20	1.60
x_t^{t+1}	0.20	0.90	0.30	2.20	2.20	2.30	3.00	3.40	2.40	2.10	1.60
x_t^{t+8}	0.50	1.20	0.20	2.00	3.20	3.20	4.40	3.10	1.70	2.20	2.10
x_t^f	1.13	1.83	0.84	1.84	2.55	2.54	3.37	3.86	2.41	2.98	2.73

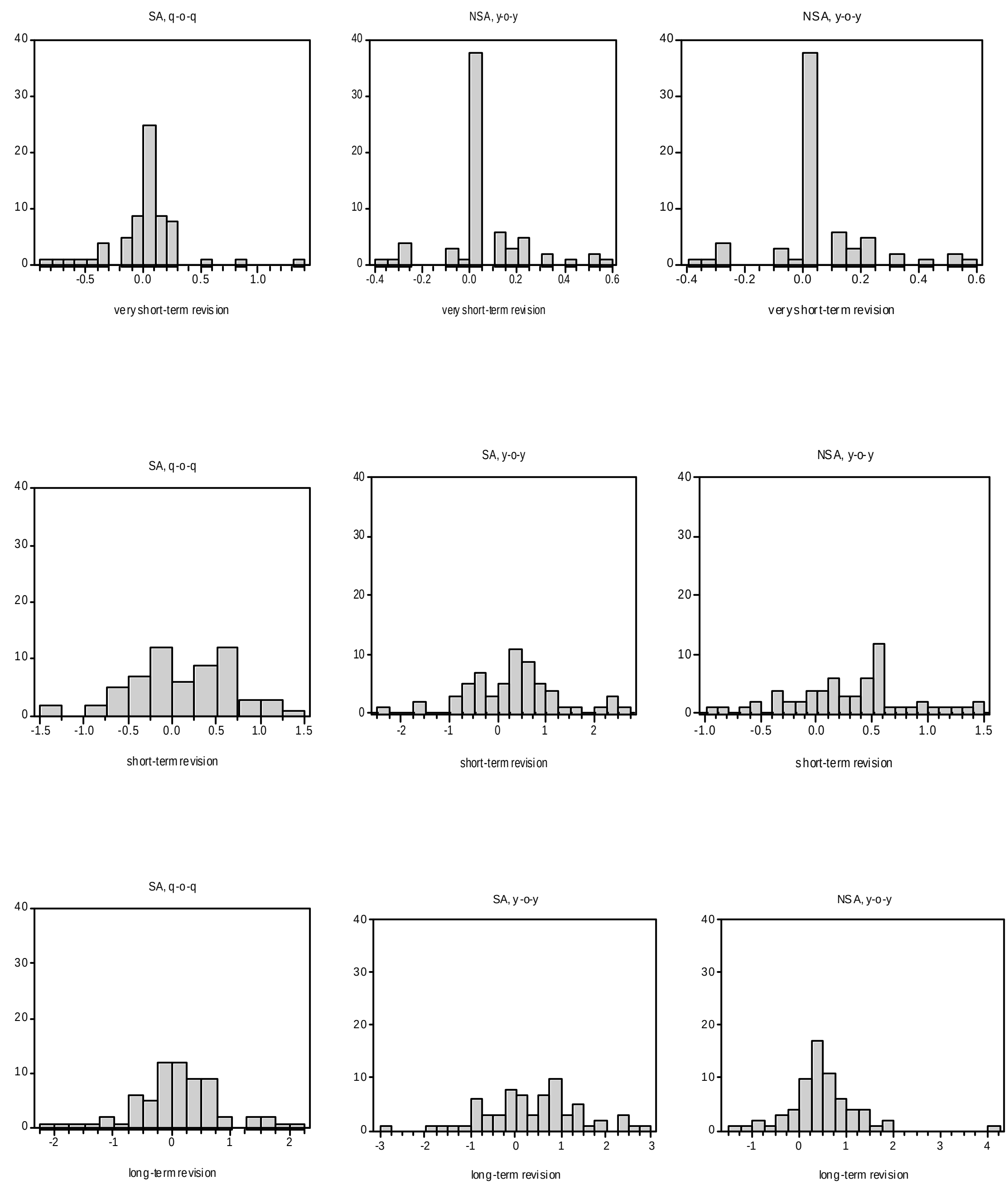
Table III *Continued*

	1996.1	1996.2	1996.3	1996.4	1997.1	1997.2	1997.3	1997.4	1998.1	1998.2	1998.3
x_t^p	1.80	3.10	3.00	3.00	2.10	3.10	2.90	3.80	4.30	3.78	3.16
x_t^{t+1}	1.40	3.10	3.10	3.00	2.60	3.10	3.10	3.80	4.87	3.71	3.16
x_t^{t+8}	2.20	3.40	3.40	3.50	3.36	3.65	3.39	4.39	4.88	3.64	3.72
x_t^f	1.88	3.54	3.42	3.29	3.49	3.83	3.63	4.37	5.52	4.26	3.79

	1998.4	1999.1	1999.2	1999.3	1999.4	2000.1	2000.2	2000.3	2000.4	2001.1	2001.2
x_t^p	3.32	3.01	3.14	3.55	4.59	4.72	4.09	3.25	2.80	1.61	1.45
x_t^{t+1}	3.32	2.98	3.14	3.55	4.59	4.89	4.09	3.46	2.80	1.35	1.45
x_t^{t+8}	3.83	3.21	3.27	3.68	4.78	4.71	3.91	2.91	1.99		
x_t^f	3.88	3.36	3.53	3.98	5.07	4.53	3.91	2.91	1.99	1.68	1.74

	2001.3	2001.4	2002.1	2002.2	2002.3	2002.4
x_t^p	0.80	0.41	0.22	-0.02	0.55	0.12
x_t^{t+1}	0.97	0.41	-0.08	-0.02	0.75	0.12
x_t^{t+8}						
x_t^f	1.08	0.57	-0.11	0.24	0.75	0.12

APPENDIX B HISTOGRAMS OF THE REVISIONS



APPENDIX C RELATIONSHIP BETWEEN SA DATA AND NSA DATA

Lemma:

Assume the non-seasonally (=NSA) series x_t^p *is a rational predictor of a "true" NSA series* x_t^f *, hence* $E\left(x_t^p - x_t^f \,\middle|\, I_{t-1}\right) = 0$ *where* $I_{t-1} = \left(x_{t-1}^p, \ldots, x_{t-h}^p, x_{t-1}^f, \ldots, x_{t-h}^f\right)$ *for some time horizon* h*. Moreover, we assume that the preliminary seasonal terms* s_t^p *used to seasonally adjust* x_t^p *are a rational predictor of the "true" seasonal terms* s_t^f *used to seasonally adjust* x_t^f*, hence* $E\left(s_t^p - s_t^f \,\middle|\, I_{t-1}\right) = 0$ *where* $I_{t-1} = \left(s_{t-1}^p, \ldots, s_{t-h}^p, s_{t-1}^f, \ldots, s_{t-h}^f\right)$ *for some time horizon* h*. If, we assume that the NSA data are equal to a seasonally adjusted (=SA) figure* xs_t *plus an additive seasonal, we have the following two formulas:* $x_t^p = xs_t^p + s_t^p$ *and* $x_t^f = xs_t^f + s_t^f$*.*

Proof:

The two assumptions that the preliminary NSA data and the preliminary seasonal terms are rational with the given two formulas imply the following:

$$\left.\begin{aligned} E\left(x_t^p - x_t^f \,\middle|\, I_{t-1}\right) = 0 \\ E\left(s_t^p - s_t^f \,\middle|\, I_{t-1}\right) = 0 \end{aligned}\right\} \Rightarrow E\left(\left(x_t^p - s_t^p\right) - \left(x_t^f - s_t^f\right) \middle| I_{t-1}\right) = 0 \Leftrightarrow E\left(xs_t^p - xs_t^f \,\middle|\, I_{t-1}\right) = 0$$

and

$$\left.\begin{aligned} E\left(xs_t^p - xs_t^f \,\middle|\, I_{t-1}\right) = 0 \\ E\left(x_t^p - x_t^f \,\middle|\, I_{t-1}\right) = 0 \end{aligned}\right\} \Rightarrow E\left(\left(x_t^p - xs_t^p\right) - \left(x_t^f - xs_t^f\right) \middle| I_{t-1}\right) = 0 \Leftrightarrow E\left(\left(s_t^p - s_t^f\right) \middle| I_{t-1}\right) = 0$$

So, it is easily proven that the SA series xs_t^p are also a rational predictor of the "true" series xs_t^f if and only if the preliminary seasonal terms s_t^p are a rational predictor of the "true" seasonal terms s_t^f.

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