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The Use of Qualitative Business Tendency Surveys for Forecasting Business Investment in Germany

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Abstract

Investment in equipment and machinery is a very important component of GDP. In this paper we examine whether data from business tendency surveys are useful for a timely assessment of current investment behavior. In addition we investigate whether the survey results are helpful for forecasting investment growth in the short run. The first question is addressed with the help of spectral analysis. To study the forecast ability we estimate linear autoregressive and additive autoregressive models. The forecasting performance is assessed through filtered residuals. The analyses show that the business survey is indeed a useful tool for assessing investment in equipment and machinery.

JEL Code: C2, C4

Keywords: Business tendency surveys, forecasting, investment, linear autoregression, additive autoregression

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1 Introduction

For forecasters, investment in machinery and equipment is a very important variable to predict. It is an essential component of domestic demand and therefore relevant for business cycle monitoring. In general, the amount of investment is also of interest, because it is the basis for further growth in the future. This paper focus on the cyclical behavior of investment in machinery and equipment, which is relevant for business cycle analysis. The aim is to achieve reasonable short-term forecasts. A valuable tool, which is also comprehensible for nonspecialists, is the business tendency survey. Common approaches of investment modeling include independent variables like output, capital stock, real user costs of capital and interest rates. Unfortunately, the usefulness of these models for short-term forecasting is limited (see e.g. Oliner, Rudebusch, Sichel, 1995).

Business tendency surveys are a widely used and accepted tool for obtaining timely signals on the economic developments. Various composite indicators are constructed with these data. Usually GDP is forecast with the help of these indicators. We use the results on a specific question to assess the year-on-year growth (strictly speaking log fourth differences) of investment in machinery and equipment. The survey question is: ”We assess our current technical capacities with regard to our current stock of orders and the expected stock of orders for the next 12 months as too large/ sufficient/too small”. Net balances of the responses ”too large” and ”too small” assessments are calculated. Since the third quarter of 1992 Ifo has included this question in its regular business survey once every quarter.
Data about investment are published by the Statistical Office quarterly and Ifo asks a question about capacity assessment quarterly as well. But Ifo includes this question in its surveys in the first month of the respective quarter. Hence the results are published in the last week of the first month of the quarter under consideration. In contrast, the quantitative data are published

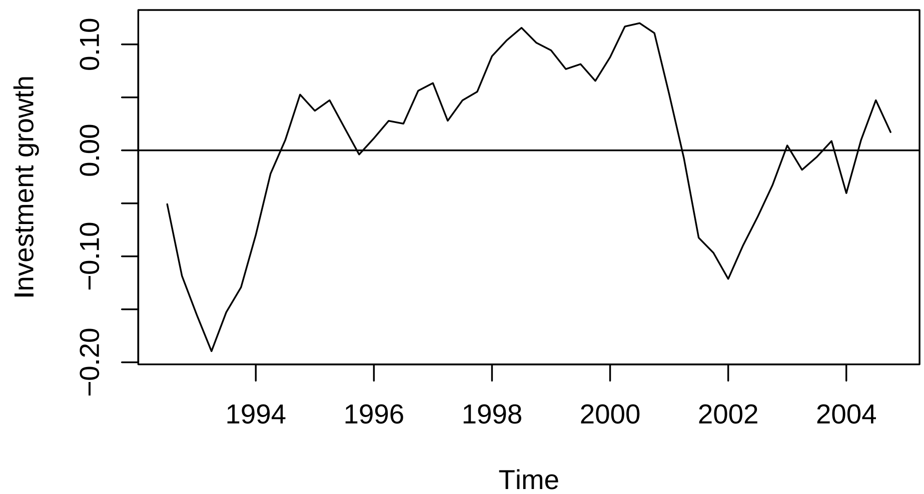

Figure 1: Year-on-year growth rates of quarterly real investment in machinery and equipment from III 1992 to IV 2004

by the Federal Statistical Office about 55 days after the end of the considered quarter. So there is a considerable publication lead of the Ifo results of about 16 weeks.

Figure 1 contains the quarterly time series of year-on-year growth of seasonal adjusted real investment in Germany. There are two pronounced dips in the years 1993 and 2002. Between these marked troughs the growth rates rose, with smaller ups and downs. For shorter notation in the following this series is denoted by ”investment” only.

The survey results multiplied by -1 are shown in Figure 2. The sign of the balances is reversed because then they are comparable with the investment

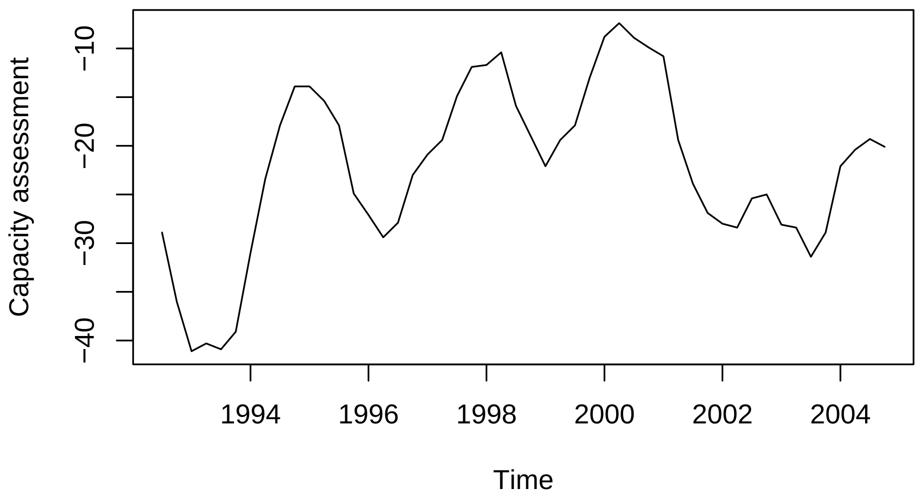

Figure 2: Balances from capacity assessments (sign reversed) from III 1992 to IV 2004

series. The two time series show similar general characteristics, although the series of survey results reveals a more pronounced cyclical component. This behavior is confirmed by spectral analyses which are presented in Section 2. Whether the survey results are helpful for forecasting changes in investment growth is considered in Section 3. Autoregressive models are used for forecasting. To allow for more flexible models than only linear ones, additive models are also considered. Section 4 summarizes the findings.

2 Spectral analysis

The two time series under consideration are both analyzed with the help of spectral analytic methods. The upper two graphs in Figure 3 contain the smoothed periodograms of the two series. The series have a similar periodic pattern except for a stronger cyclical component of the survey series around frequency 0.1. For quarterly data a frequency of 0.1 implies a component of a 2.5 year period. This more pronounced cyclical behavior is also visible from the time series in Figure 1 and 2, as already mentioned in the previous section. The connection between the two time series can be investigated more closely with estimated coherence, which is drawn in the third graph of Figure 3. There is a positive coherence between the two series for the business-cycle relevant frequencies. The phase spectra of the two series is not plotted here because it shows no phase shift of the two series. Also the cross-correlation function indicates a coincident relationship between the two series and is not plotted here too. However the survey results have a publication lead of about 16 weeks.

Since there are only data for a time span of seven years available, we will focus in the sequel on shorter cyclical components. Therefore, the first differences of the two time series are considered. The two smoothed periodograms of these series are contained in Figure 4. They show that in both series the main cyclical component is of a frequency of about 0.1. As before, there is also a positive coherence around this frequency, pointing to a connection between the two series around this frequency.

Business tendency surveys are intended to give early signals about the business cycle course. Visual inspection of the considered time series and exploratory analysis with spectral methods confirm that the qualitative question about capacity assessment in a business survey is a valuable tool to obtain early signals, especially for the cyclical component of investment, which is of importance for business cycle analysis and forecasting. But for the in-

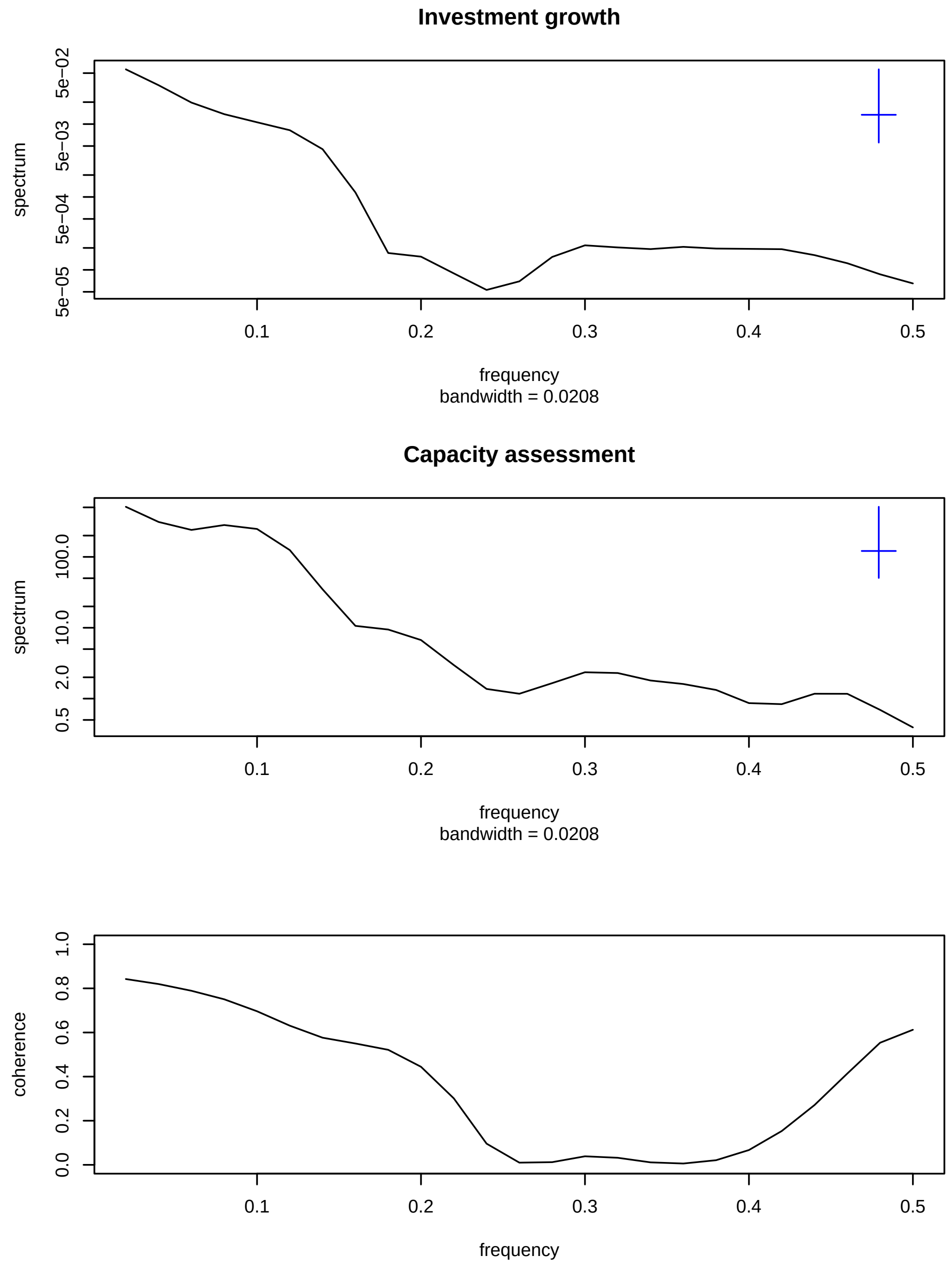

Figure 3: Estimated spectra and coherence for growth of investment and capacity assessments

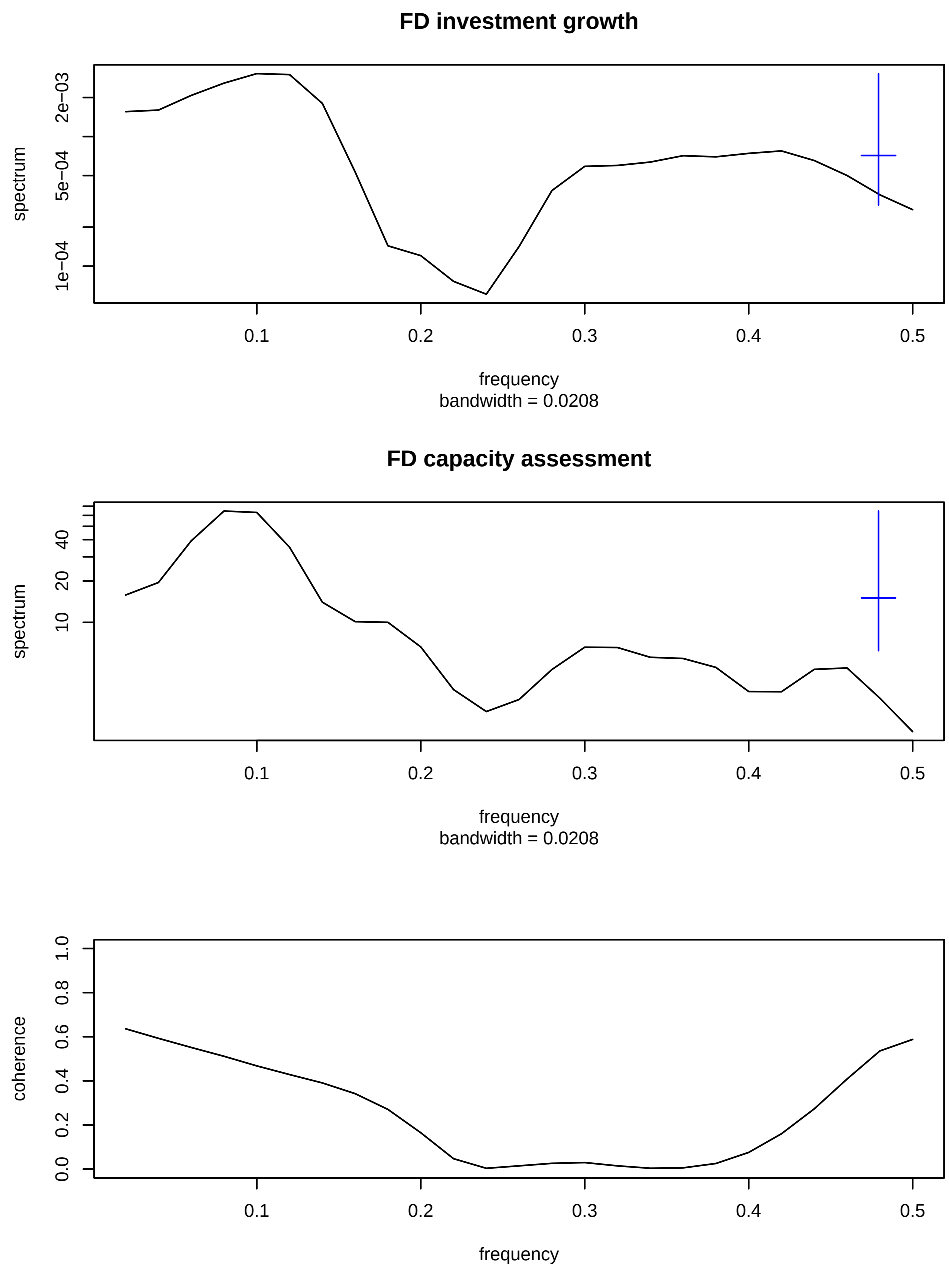

Figure 4: Estimated spectra and coherence for the first differences of growth of investment and capacity assessments

terpretation of the results, it should be kept in mind that the time series of the balances usually shows a more pronounced cyclical behavior. The main advantage of the business tendency surveys is that the results are in general published in a very timely fashion. So monitoring the time series of the survey results helps to assess the investment activity of the industry at an early stage.

3 Linar and additive autoregressive analysis

The results from business tendency surveys are often used to obtain insights into the current and future course of the economic cycle. Hints for turning points, accelerations or decelerations are searched. The above considerations show that the survey results are useful in this respect. This section focuses on the question of whether the survey results are even useful for forecasting the quantitative development of investment. A common approach to shed light on this question consists of two steps. First an AR model for the target variable is chosen and estimated. Then the potential indicator is added as an independent variable into the model. The indicator is considered as useful when the model fit is improved significantly.

In this section we focus on analyzing the first differences of year-on-year growth of investment. This series was also investigated in the previous section. It shows a cyclical behavior which is relevant for business cycle analysis. Visual inspection, as well as common unit root tests, leave no doubt that the time series is not integrated. Therefore the formal test results are not presented here. The information criteria AIC and SIC both suggest an AR model with lag 1 and lag 4. Table 1 contains the parameter estimates and inference for this univariate time series model.

Table 1: Estimated linear autoregressive models

Model A:	$y_t = \alpha_1 y_{t-1} + \alpha_4 y_{t-4} + u_t$	
Parameter	Estimate	p-Value
α_1	0.37251	0.0055
α_4	-0.37984	0.0044
$R^2_{adj} = 0.272$		AIC= -194.405

Model B:	$y_t = \alpha_1 y_{t-1} + \alpha_4 y_{t-4} + \beta_1 x_{t-1} + u_t$	
Parameter	Estimate	p-Value
α_1	0.14827	0.24317
α_4	-0.40591	0.00065
β_1	0.00413	0.00039
$R^2_{adj} = 0.448$		AIC= -206.025

To analyze whether the survey results are able to improve the fit of the univariate AR model, lags of the survey balances are added to the model. Table 1 also contains the results for this model. The only lag which has a significant coefficient is the lag 1. Adding this variable to the model leads to an improvement of adjusted R^2 from 0.272 to 0.448. Comparing the two models with the F statistic leads to a value for the F statistic of 14.845 and an associated p-value of 0.00039, rejecting the Null hypotheses that the survey balances do not Granger cause investment. Clearly, in this respect causality does not mean a causal relationship but indicates the usefulness of the balances for forecasting. It is remarkable that the inclusion of the survey series leads to an insignificant α_1. Thus this inclusion makes the first lag of the investment series unnecessary and additionally improves the fit of the model remarkably. This is appealing because the quantitative investment data is not only published much later than the survey results but additionally they often must be revised. The survey data, in contrast, is subjected only to minor revisions.

Assessing the usefulness of an estimated model for forecasting with statistics based on in-sample calculations is risky, because the predictability is usually overstated. A popular approach to assess a model is to use out-of-sample forecast errors. The time series is divided into two parts and the first part is used for estimation. The estimated model is then evaluated out-of-sample with the data of the second part. This procedure is often applied in a rolling fashion, using all data before the time point at which an out-of-sample forecast is calculated for model estimation. But in the present study this approach is not feasible, because the underlaying time series are too short. The model uncertainty introduced by estimating the model with only a few observations would be large, leading to excessive forecast variation. So in-sample forecast variation would overstate and out-of sample forecast errors would understate the true performance of the model. A feasible way to assess the forecast performance in cases like the present one was recently suggested by Pena and Sanchez (2005). In their analysis, they focus on the mean square prediction error (MSPE) and argue that the usual in-sample MSPE has a negative, large-sample bias and for the out-of-sample MSPE the asymptotic bias is positive. Therefore, the authors suggest an approach based on filtered residuals, which leads to an estimator of MSPE that has an large-sample bias of lower order of magnitude than its competitors.

To assess the above estimated model according to the one-step prediction behavior, the two models

$$y_t = \alpha_1 y_{t-1} + \alpha_4 y_{t-4} + u_t + w_{t1} D_t^{T+1} \quad (1)$$

$$y_t = \alpha_4 y_{t-4} + \beta_1 x_{t-1} + u_t + w_{t2} D_t^{T+1} \quad (2)$$

are estimated for T=5,...,n-1. D are dummy variables with $D_t^{t_0} = 1$, if $t = t_0$ and $D_t^{t_0} = 0$ otherwise and w_{t1}, w_{t2} parameters corresponding to these variables. The estimators for the one-step-ahed MSPE are

$$\hat{V}_1 = \frac{\sum_{t=5}^{n-1} w_{t1}^2}{n-5} \quad (3)$$

$$\hat{V}_2 = \frac{\sum_{t=5}^{n-1} w_{t2}^2}{n-5}. \quad (4)$$

The resulting estimations for the investment data are $\hat{V}_1 = 0.0006720058$ and $\hat{V}_2 = 0.0005401997$, so including the survey variable in the model leads to a reduction in the estimated MSPE of about 19.6%.

To allow a more flexible structure, additive models can be considered. Additive models have become a quite popular nonparametric technique, also because of the monograph by Hastie and Tibshirani (1990). In the times series context these model are discussed for example in Fan and Yao (2003). They denote the model

$$y_t = s_1(y_{t-1}) + ... + s_p(y_{t-p}) + u_t \tag{5}$$

by AAR(p) which is the abbreviation for "additive autoregressive model". $s_1, ..., s_p$ are univariate functions which might be estimated by nonparametric regression techniques. In the following an implementation of Simon N. Wood is used. See Wood (2001) for a description of the estimation procedure. To estimate the unknown univariate functions, penalized regression splines are used. As usual in nonparametric regression, estimation requires the choice of a smoothing parameter. The appeal of Wood‘s algorithm is that the smoothing parameters of each term in the model are chosen simultaneously as part of model fitting by minimizing the generalized cross validation (GCV) score of the whole model. After estimation, approximate tests can be used to assess the estimated model and to compare the results for different models. Table 2 contains the results for an AAR model including lags 1 and 4. The column denoted degrees of freedom contains the estimated degrees of freedom of the computed nonparametric regression. A degree of freedom of 1 would imply that a linear function is chosen by the fitting procedure. For both autoregressive terms nonlinear functions are estimated, which leads, compared to Model A, to an improved fit. The difference between adjusted R^2 for the additive Model C and the Model A is 0.131. But the approximate value of the F-statistic is only 2.3156 with an associated p-value of 0.05147. Notice also that the increase in R^2 is not sufficient to outperform the linear

Model B.

Table 2: Estimated additive autoregressive models

Model C:	$y_t = s_1(y_{t-1}) + s_4(y_{t-4}) + u_t$	
Varable	Degrees of Freedom	p-Value
y_{t-1}	6.516	0.012479
y_{t-4}	1.754	0.0054054
$R^2_{adj} = 0.403$		AIC= -196.8549

Model D:	$y_t = s_1(y_{t-1}) + s_4(y_{t-4}) + s_x(x_{t-1}) + u_t$	
Parameter	Degrees of Freedom	p-Value
y_{t-1}	1	0.2767
y_{t-4}	1	0.0006997
x_{t-4}	1	0.0004913
$R^2_{adj} = 0.448$		AIC= -205.001

Next the survey results are added as variables to the additive model. The GCV score is minimized by the linear model. Allowing for an additive structure instead of only a linear one does not lead to gains. Thus the linear approach is sufficient. With the help of the business tendency survey it is possible to build an easy and valuable model for predicting changes in investment growth. Subsidizing the first lag of first differences of the survey variable into the linear model, instead of the same lag of the first differences of real investment growth, improves the model fit remarkably. In addition, this replacement leads to estimates that are less subjected to revisions of the quantitative data.

4 Summary

Investment is a component of GDP which is quite volatile over the business cycle. Therefore there is a strong need for timely indicators that signal changes in investment behavior. Since 1992, the Ifo Intitute has added a question about capacity assessment once every quarter to its business tendency surveys. Visual comparison as well as spectral analysis confirms that the result of this qualitative question is a valuable indicator, especially for the cyclical variation of investment. This is also confirmed when autoregressive models for the first differences of the year-on-year investment growth rates are estimated. The Null hypothesis that the survey balances do not Granger cause is rejected, and a method for predictive validation suggested by Pena and Sanchez (2005) shows that adding the balances to an purely autoregressive model improves the forecasts. Further improvements of model fits might result from fitting additive instead of linear models. Additive models allow for much more flexible structures than linear models. But the estimation results show that the linear approach is sufficient. Overall, the calculations show that the qualitative question about capacity assessment in business surveys is a valuable tool for the assessment of investment. The survey results are published in a timely fashion and are subjected to only minor revisions.

5 References

Fan, J., Yao, Q. (2003): Nonlinear Time Series. Springer, Heidelberg.

Hastie, T.J., Tibshirani, R.J. (1990): Generalized Additive Models. Chapman and Hall, New York.

Oliner, S., Rudebusch, G., Sichel, D. (1995): New and Old models of Business Investment: A Comparison of Forecasting Performance. Journal of Money, Credit and Banking, 27, 806-826.

Pena, D., Sanchez, I. (2005): Multifold Predictive Validation in ARMAX Time Series Models. Journal of the American Statistical Association, 100, 135-146.

Wood, S.N. (2001): mgcv: GAMs and Generalized Ridge Regression for R. R News 1/2, 20-25, downloadable from www.r-project.org.

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