NONPARAMETRIC REGRESSION AND THE DETECTION OF TURNING POINTS IN THE IFO BUSINESS CLIMATE

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Abstract

Business climate indicators are used to receive early signals for turning points in the general business cycle. Therefore methods for the detection of turning points in time series are required. Estimations of slopes of a smooth component in the data can be calculated with local polynomial regression. A change in the sign of the slope can be interpreted as a turning point. A plug-in method is used for data-based bandwidth choice. Since in practice the identification of turning points at the actual boundary of the time series is of special interest, this situation is discussed in more detail. The nonparametric approach is applied to the Ifo Business Climate to demonstrate the application of the nonparametric approach and to analyze the time lead of the indicator.

JEL Code: C14, C22, C42.

Keywords: Nonparametric regression, slope estimation, turning points, business climate indicators.

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1 Introduction

Leading economic indicators are used to predict turning points in business cycles. A turning point of the general business cycle can be predicted by timely detection of the turns in a leading indicator. By applying methods for detecting turning points in a leading indicator we can receive early signals for the future behavior of the business cycle.

Once an indicator is formed, historical data are used to compare the turning points of the indicator and the reference cycle. This can be done by observing the leads and lags of the indicator with respect to the turning points. However, the problem is that the peaks and troughs have to be defined. On the other hand one has to decide with actual data whether a turning point occurs or not on the base of observations from the past until today. Thus decisions about the behavior of the time series at its right boundary are required.

There are various methods which are applied to detect turning points in leading indicators. They range from rules which are very simple to apply, like the three-times rule, to very sophisticated models like hidden Markov models, which for example are discussed in Andersson et al. (2004) and Koskinen, Öller (2004). The three times rule goes back to Vaccara and Zarnowitz (1978) and defines a signal of change when the indicator shows a change in direction of movement for at least three consecutive months.

In this article methods from nonparametric regression analysis are used to detect turning points. The advantage of these methods is that they are based on well established statistical theory and that they do not need very strong model assumptions. Since a turning point occurs when the sign of the slope of the smooth time series component changes, this article focuses on nonparametric slope estimation. Bevor this procedure is described, in Section 2 the Ifo Business Indicator is discussed in more detail. Then in Section 3 the nonparametric estimation method is presented. Section 4 contains the results of the nonparametric method applied to the Ifo data. For comparison results for a hidden Markov model and a structural time series model are also given. The last Section summarizes the findings.

2 The Ifo Business Climate and reference turning points

With the Ifo Business Climate the Ifo Institute presents monthly data on economic development in Germany. The data from the enterprise surveys in construction, commerce and manufacturing are closely observed by business leaders, financial institutions and politicians. The Ifo Business Climate is exclusively based on qualitative questions, which are answered by the enterprises of the survey panel monthly. The questions have two chronological components referring to the present and to the future. Using these two components the business climate is calculated (see Oppenländer and Poser 1989). Figure 1 contains the time series of the deseasonalized Ifo Business Climate ranging from January 1969 to May 2004 (n=425). This time series is the basis of the considerations in this article, although, from a statistical point of view, it is not satisfactory to work with deseasonalized series. But in many institutes standard procedures to handle the seasonal component are used and conclusions are made on basis of these series.

In order to check the informative quality of the indicator for economic growth, an obvious approach is to compare these qualitative assessments with the real economy. For this analysis the gross domestic product (GDP) could be chosen. But GDP is published only quarterly, so GDP and the Ifo Business Climate indicator have different publication cycles. A suitable reference series which is published monthly is industrial production. The Deutsche Bundesbank and also the OECD have developed rules to define turning points. Based on these rules Hott, Kunkel and Nerb (2004) determine the turning points for Germany as listed in Table 1.

With these turning points in mind the behavior of the Ifo Business Climate series can be considered. Hott et al. (2004) give the following interpretation:

“ when we take a closer look at the relationship between the business climate and the turning points, there are four striking episodes. First, there seem to be already a little trough in the beginning of 1974. An explanation for this could be that following the crises in 1973 the government tried to

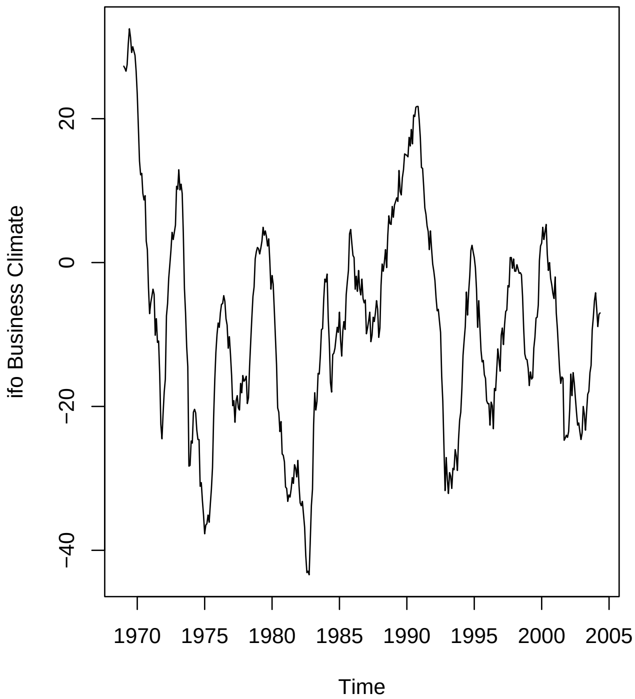

Figure 1: Monthly Ifo Business Climate from January 19969 to May 2004 (n=425)

push the economy with an expansionary policy. But success of these steps was rather short term. Second, there seems to be an additional cycle between the trough in 1975 and the peak in 1980. The reason for this might be a special effect from some high new orders in July 1976, which are also reflected by industrial production but do not define an extra peak. Third, there is also a mimic cycle between the trough in 1982 and the peak in 1985. This cycle resulted mainly from strikes in 1984 and is also reflected by industrial production. Fourth, the peak in 1992 seems to be already indicated by the business climate in 1990. The reason for this might be the extra demand resulting from German reunification. When we evaluate the predictive value of the Ifo Business Climate, we have to take these points into account."

Turning points	
Peak	Trough
March 1970	November 1971
April 1973	May 1975
January 1980	November 1982
November 1985	March 1988
March 1992	November 1993
December 1994	February 1996
March 1998	February 1999
December 2000	

Table 1: Defined turning points of monthly industrial production in Germany

In order to check the easy to use three times rule the results for this method are listed in Table 2. As can be seen, each of the cycles in the reference series are also detected in Ifo series. In addition there are 3 cycles signaled. Some of these extra cycles can be explained by the special situations discussed above. It will be interesting to see whether the other methods lead to better results than this simple but popular rule.

3 Local polynomial regression and slope estimation

In this article nonparametric regression methods are used to detect turning points. There are various methods of nonparametric estimation. One of the most popular with appealing asymptotic properties is the local polynomial regression estimator. See Fan and Gijbels (1996) for a monograph about this method. Local polynomial regression is used in the sequel because it also allows easy estimation of slopes. The business indicator helps to establish whether the economy is in a recession phase or in a expansion phase. Not the level is of interest but the direction of the economic course. That is why estimation of the slope is the appropriate procedure.

Est. turning points with the three times rule	
Peak	Trough
12.96 (+3)	3.71 (-)
11.71 (-)	2.72 (-3)
7.73 (-3)	4.75 (+1)
9.76 (-)	6.78 (-)
4.80 (-3)	1.83 (-2)
5.84 (-)	9.84 (-)
2.86 (-3)	4.87 (+11)
2.90 (+25)	1.94 (-2)
2.95 (-3)	6.97 (-4)
9.98 (-6)	7.99 (-5)
8.00 (+4)	3.02
8.02	7.03

Table 2: Ifo Business Climate turning points estimated with the three times rule (monthly leads in brackets)

Consider the equidistant design nonparametric regression model

$$Y_i = g(t_i) + \epsilon_i, \tag{1}$$

where $t_i = (i - 0.5)/n$, $g : [0, 1] \rightarrow R$ is a smooth function and ϵ_i is the innovation process with mean 0 and common variance σ^2.

Assume that g is at least $(p+1)$-times differentiable at a point t_0. Then $g(t)$ can be approximated locally by a polynomial of order p:

$$g(t) = g(t_0) + g'(t_0)(t - t_0) + ... + g^{(p)}(t_0)(t - t_0)/p! + R_p \tag{2}$$

for t in a neighborhood of t_0, where R_p is a remainder term. Given n observations $Y_1, ..., Y_n$ an estimator of $g^{(v)}$ $(v \leq p)$ can be obtained by solving the locally weighted least squares problem

$$Q = \sum_{i=1}^{n} \left\{ Y_i - \sum_{j=0}^{p} \beta_j (t_i - t_0)^j \right\}^2 K\left(\frac{t_i - t_0}{h}\right) \Rightarrow \min, \tag{3}$$

where h is the so called bandwidth and K is a kernel function (a symmetric density having compact support $[-1, 1]$). Let $\hat{\beta} = (\hat{\beta}_0, \hat{\beta}_1, ..., \hat{\beta}_p)^T$ be the solutions of (3), than $v!\hat{\beta}_v$ estimates $g^{(v)}(t_0)$, $v = 1, ..., p$.

As kernel function the Epanechnikov weight function $K(u) = (3/4)(1 - u^2)1_{(-1,1)}(u)$ is often used which is asymptotically optimal for estimating $g^{(v)}(t_0)$ (see Fan and Gijbels, 1996). Seifert and Gasser (1996) showed that the Gauss kernel has appealing properties in finite samples and therefore in our simulations we computed estimates with this kernel.

According to asymptotic theory $(p - v)$ should be odd. Beran and Feng (2002) showed that a local polynomial estimator with $(p - v)$ odd has automatic boundary correction. This is an important feature particularly in time series smoothing, where the right boundary is often the current value of the series. In this article $p = 2$ is used for the estimation of the first derivative, which is a common approach. There remains the choice of a bandwidth h which is always the crucial point in nonparametric regression.

For databased bandwidth choice a so called "plug-in" algorithm is used. A measure for assessing the performance of $g^{(v)}$ is the mean averaged squared error (MASE):

$$M(h) = n^{-10} \sum_i E[\hat{g}_h^{(v)}(t_i) - g^{(v)}(t_i)]^2. \tag{4}$$

The plug-in procedure grounds on the asymptotic mean average squared error (AMASE) and the "optimal" bandwidth is the one which minimizes the AMASE. Since this optimal bandwidth depends on unknown quantities as for example $g^{(3)}(t)$ an algorithm which provides estimates of these unknown quantities has to be developed. Gasser, Kneip and Köhler (1991) proposed an iterative plug-in algorithm. An iterative algorithm especially for estimating the first derivative is described in Gerard and Schucany (1997). The method consists of the following steps:

1. Set $h_0 = 2/n$.

2. Iterate the following step for $i = 1, ..., 16$:

$$h_i = \left(\frac{3}{4n} \cdot \frac{V_1 \hat{\sigma}^2}{B_1^2 (\int_0^1 w(t)(\hat{g}^{(3)}(t; h_{i-1} n^{1/14}))^2 dt)} \right). \tag{5}$$

3. Stop after 16 iterations and set $h = h_{16}$.

The constants V_1 and B_1 are from expressions of the asymptotic bias and variance, which under general regularity conditions are

$$bias[\hat{g}^{(1)}(t)] \approx \frac{1}{6} g^{(3)}(t) \frac{k_4}{k_2} h^2 = B_1 g^{(3)}(t) h^2 \tag{6}$$

$$var[\hat{g}^{(1)}(t)] \approx \frac{\sigma^2}{nh^3 k_2^2} \int_{-1}^{1} K^2(u) du = \frac{\sigma^2 V_1}{nh^3}, \text{ where} \tag{7}$$

$$k_i = \int_{-1}^{1} u^i K(u) du. \tag{8}$$

The estimate of the third derivative is obtained from the coefficient of the cubic term of a locally weighted third-order fit. The function $w(t)$ is a weight function used to eliminate boundary effects and σ^2 is estimated with

$$\hat{\sigma^2} = \frac{2}{3(n-2)} \sum_{i=2}^{n-1} (Y_i - \frac{1}{2} Y_{i-1} - \frac{1}{2} Y_{i+1})^2, \tag{9}$$

which was proposed by Gasser, Sroka and Jennen-Steinmetz (1986).

4 Application to Ifo Business Survey data

At first, the nonparametric approach is applied to the whole series of the Ifo Business Climate ranging from January 1969 to May 2004 (n=425). This allows the estimation of turning points in the history of the series. The estimation results for the slope are shown in Figure 2 and the dating of the turning points (slope=0) are contained in Table 3. For the calculations the package "locfit" from Loader (1999) for the statistical computing language R (www.r-project.org) is used.

All reference cycles are indicated. There is a lead 10 times and 5 times there is a lag. The Ifo Business Climate seems to be a suitable indicator particularly when it is taken into account that the official statistics are published with a time delay.

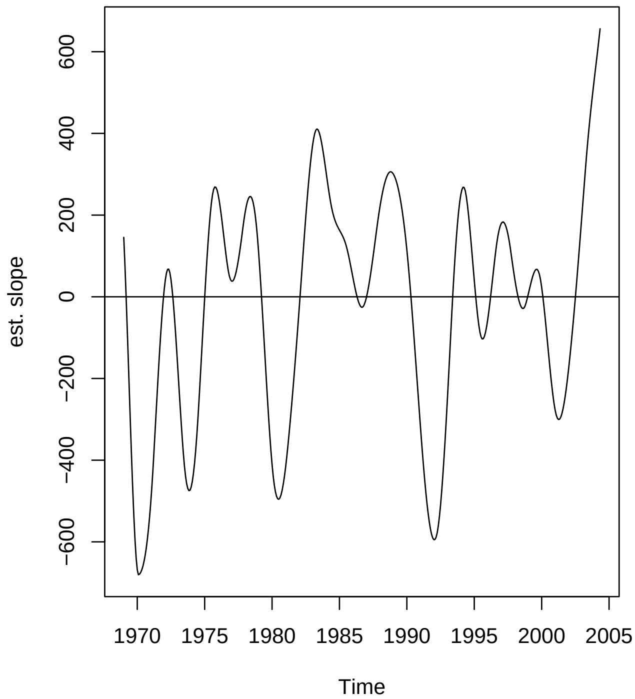

Figure 2: Estimated slope for the Ifo Business Climate

Smoothing the whole time series may help to date past turning points. But interesting for the business analyst is the situation at the actual date or in other words at the right boundary of the time series. To consider this situation rolling estimates are used. This is realized as follows: The nonparametric procedure is applied to the first 120 observations (10 years) and the slope estimate for the last point (t=120) is marked. Then the window of 120 observations is moved one step to the right and the slope estimation for the last time point in the window (t=121) is noted. The window of observations is moved further until a slope estimation or the last time point is calculated. At each step a new bandwidth is calculated with the above described algorithm but the bandwidths calculated until a specific time point are smoothed to reduce variability. So the bandwidth used for slope estimation is a bandwidth which results from smoothing the actual and the past

Est. turning points	
Peak	Trough
6.1969 (+9)	1.1972 (-2)
9.1972 (+7)	2.1975 (+3)
4.1979 (+9)	2.1982 (+9)
5.1986 (-6)	2.1987 (+13)
5.1990 (+22)	6.1993 (+5)
3.1995 (-3)	4.1996 (-2)
4.1998 (-1)	1.1999 (+2)
3.2000 (+9)	8.2002

Table 3: Ifo Business Climate turning points based on nonparametric slope estimation (monthly leads in brackets)

bandwidths calculated with the plug-in procedure.

The results for rolling slope estimation are shown in Figure 3. Not surprisingly the rolling estimates are more variable than the estimates resulting from smoothing the whole series. All reference cycles are detected but there are two additional cycles. One of them is the above discussed 1984 cycle which is caused by strikes. With the rolling estimation only five turning points are detected with a lead, and six turning points are detected with a lag. However, one should remember that the reference data are published only with a time delay. In addition there is the same boundary problem with the actual reference data as with the business indicator.

The above method of bandwidth choice is developed with the aim of estimating the slope function over the whole range of data in a "optimal" way. But the rolling estimates should give good estimates of the sign of the slope at the right boundary. Therefore another strategy for bandwidth choice can also be used. This method incorporates the above algorithm for rolling estimates. Within the rolling window the bandwidth calculated above is used to estimate the slope function. Then the sign of the estimated slope is marked. With one sided smoothing within the window, it is searched for the bandwidth which gives the lowest error rate regarding the sign of the slope. It is counted how often the one sided smoothing with a specific bandwidth gives

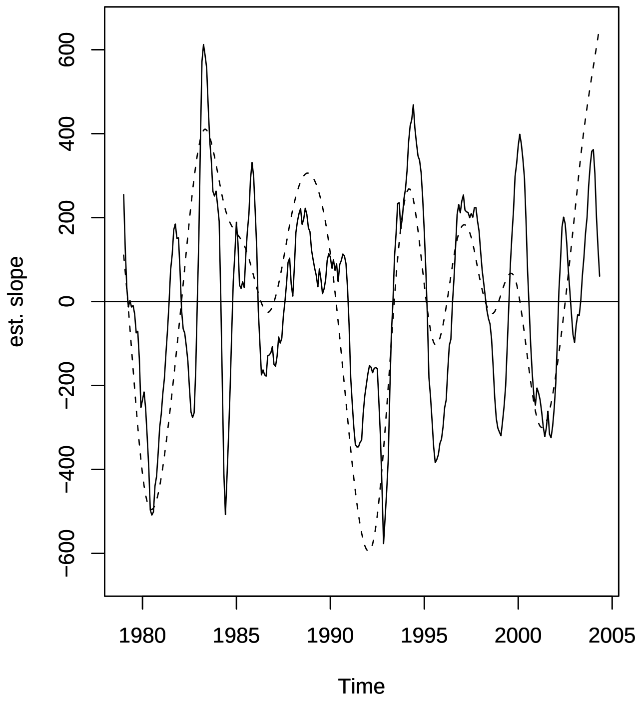

Figure 3: Rolling estimated slope with plug-in bandwidth (solid line) and smoothed slope from Figure 1 (dotted line) for the Ifo Business Climate

a different sign as the smoothed slope.

Figure 4 and Table 5 contain the results from this procedure. Compared to the previous rolling estimates the results are less smooth. Some of the turning points are detected earlier. But there is a price for that. In addition to the turning points contained in Table 5 there are some pointed peaks in the slope function which break through the zero line, for example in September 1986, Dezember 1987 or January 2001. Since these peaks are sharp they can be indicated as wrong signals very quickly. However, this example demonstrates the general decision problem: increasing the bandwidth reduces wrong signals but decreases the lead and vice versa.

Rolling est. turning points	
Peak	Trough
4.1979 (+9)	7.1981 (-)
2.1982 (-)	1.1983 (-2)
4.1984 (-)	11.1984 (-)
3.1986 (-4)	9.1987 (+6)
1.1991 (+14)	6.1993 (+5)
3.1995 (-3)	8.1996 (-6)
5.1998 (-2)	8.1999 (-6)
8.2000 (+4)	3.2002
11.2002	5.2003

Table 4: Ifo Business Climate turning points based on rolling nonparametric slope estimation and plug-in bandwidth choice (monthly leads in brackets)

To compare the nonparametric approach to other more sophisticated methods, the Ifo data are analyzed with a hidden Markov model (HMM). For a recent discussion of this kind of models, see e.g. Andersson et al. (2004). A monograph about hidden Markov models is McDonald and Zucchini (1997). The hidden Markov models rely on stronger assumptions than the nonparametric approach discussed above. The following setup is used. The model for X is

$$X_t = \mu_t + \epsilon_t, \tag{10}$$

where $\epsilon_t \sim iid\, N(0, \sigma^2)$ and

$$\mu_t = \begin{cases} \beta_0 + \beta_1 t, & t < \tau \\ \beta_0 + \beta_1(\tau - 1) + \beta_2(t - \tau + 1) & t \geq \tau \end{cases}, \tag{11}$$

where $t = 1, 2, .., n$ and τ is a turning point. A consequence of these assumptions is that for the differentiated process

$$E[X_t - X_{t-1}] = \begin{cases} \beta_1, & t < \tau \\ \beta_2 & t \geq \tau \end{cases}, \tag{12}$$

holds. The conditional distribution of X_t is determined by the unobserved (hidden) state C_t of an two-state Markov chain $\{C_t,\, t = 1, 2, ...\}$, $C_t \in \{0, 1\}$.

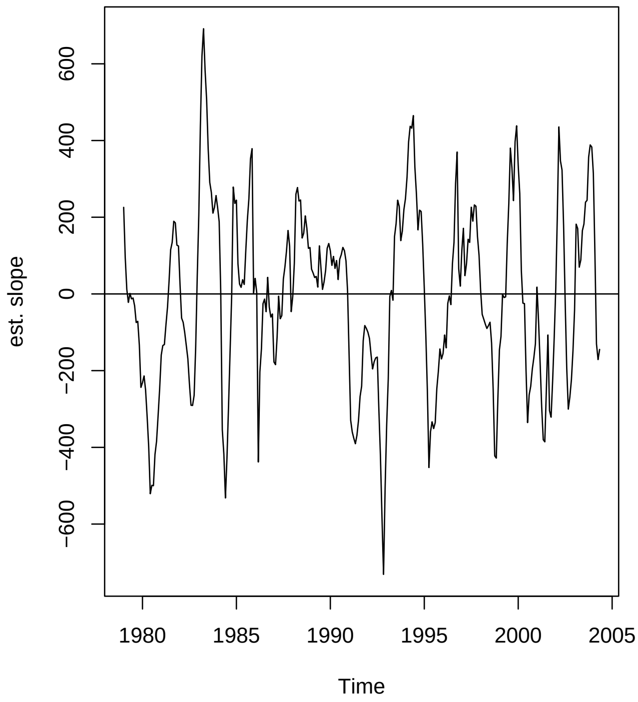

Figure 4: Rolling estimated slope with boundary bandwidth

Defining $\mathbf{X^t} = \{X_s,\, s = 1, ..., t\}$ and $\mathbf{C^{(t)}} = \{C_s,\, s = 1, ..., t\}$ the HMM assumes

$$\begin{aligned} P(X_t|\mathbf{X^{(t-1)}}, \mathbf{C^{(t)}}) &= P(X_t|C_t) \text{ “conditional independence”}, \quad (13) \\ P(C_t|\mathbf{C^{(t-1)}}) &= P(C_t|C_{t-1}) \text{ “Markov property”}. \quad (14) \end{aligned}$$

For the Ifo Business Climate index this hidden Markov model is estimated with the help of the library “repeated”, which is provided by Lindsey and Lindsey (2004). $C = 1$ indicates an expansion and $C = 0$ indicates a recession phase. At time t the state is categorized using the posterior probability. It is assumed that the current state is expansion when

$$P(C_s = 1|x_s) > 0.5 \quad (15)$$

Selected est. turning points (with boundary bandwidth)	
Peak	Trough
4.1979 (+9)	6.1981 (-)
2.1982 (-)	12.1982 (-1)
4.1984 (-)	11.1984 (-)
3.1986 (-4)	7.1987 (+8)
1.1991 (+14)	6.1993 (+5)
2.1995 (-2)	7.1996 (-5)
2.1998 (+1)	6.1999 (-4)
4.2000 (+8)	1.2002
7.2002	2.2003
3.2004	

Table 5: Selected Ifo Business Climate turning points based on rolling non-parametric slope estimation and boundary bandwidth choice (monthly leads in brackets)

holds. The whole ifo series is used for recursive estimation of the states. The results are shown in Figure 5. With respect to the figure it is obvious that these methods give too many regime switches. But are the turning points given by the rolling nonparametric method also indicated by the HMM?

Table 6 shows a selection of turning pints of the HMM relevant for this comparison. First, all turning points given by the nonparametric smoothing method are also estimated by the HMM. Sometimes the HMM indicates a turning point earlier, sometimes at the same time and sometimes a little bit later. So there is no dominating method. From Figure 5 it is also clear that more stable results are required. The solution might be the development of formal statistical tests or the use of another threshold in (15), which could be larger than 0.5 for a switch into the $C = 1$ regime and less than 0.5 for a change into the recession regime. But one should also keep in mind that such adjustments also affect the time lead of detection. As a rule, the lead will be reduced (or the lag increased). The charm of these models results from the possibility of calculating probabilities for the two states. This is a very useful tool for the interpretation of the indicator.

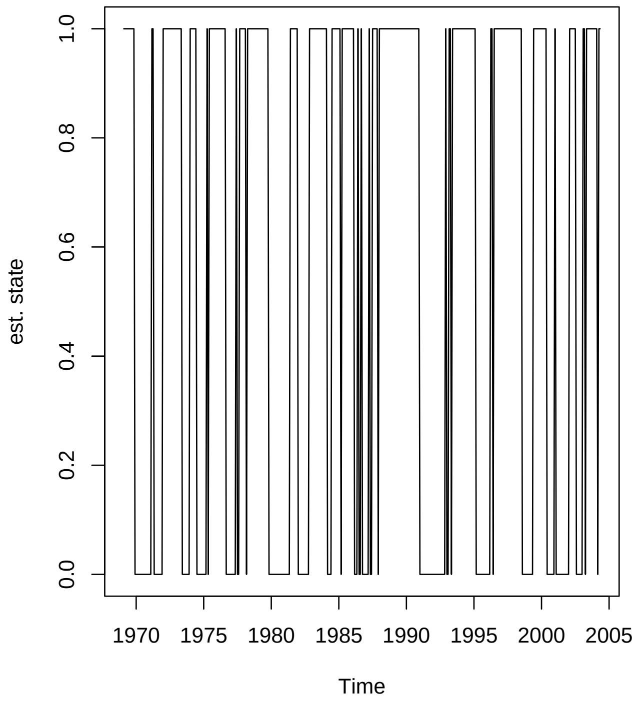

Figure 5: Estimated state (1=expansion, 0=recession) estimated with a hidden Markov model

Another class of models which can be used for slope estimation are structural time series models. These models are discussed in Durbin and Koopman (2001) and Harvey (1989). The model

$$\begin{aligned} y_t &= \mu_t + \epsilon_t, \qquad \epsilon_t \sim N(0, \sigma_\epsilon^2), & (16) \\ \mu_{t+1} &= \mu_t + \nu_t + \xi_t, \qquad \xi_t \sim N(0, \sigma_\xi^2), & (17) \\ \nu_{t+1} &= \nu_t + \zeta_t, \qquad \zeta_t \sim N(0, \sigma_\zeta^2), & (18) \end{aligned}$$

is called the local linear trend model, where y_t are the observations and μ_t, ν_t are not observed directly. Equation (16) is the observation equation and the other two are called state equations. μ_t is the local level and ν_t the local slope. If $\xi_t = \zeta_t = 0$ then $\nu_{t+1} = \nu_t = \nu$, say, and $\mu_{t+1} = \mu_t + \nu$ so the trend is exactly linear. Filtering this model gives the slope estimates shown in Figure

Selected HMM turning points	
Peak	Trough
11.1979 (+2)	6.1981 (-)
1.1982 (-)	11.1982 (0)
3.1984 (-)	7.1984 (-)
3.1986 (-4)	7.1987 (+8)
1.1991 (+14)	3.1993 (+8)
3.1995 (-3)	4.1996 (-2)
8.1998 (-5)	6.1999 (-4)
6.2000 (+6)	2.2002
8.2002	2.2003

Table 6: Selected Ifo Business Climate turning points based on estimates for a hidden Markov model (monthly leads in brackets)

6. A comparison of the estimates with the nonparametric ones confirms the results of the later one. The general course of the curves is very similar. However, the results for the structural time series model are more scattered, leading to some additional wrong change point signals.

5 Conclusion

Local polynomial modelling can be applied for regression estimation of the slope of a smooth function. Since business climate indicators are often used to get early signals about the direction of the real economy, slope estimation is a suitable aid for interpreting the indicators. Smoothing the whole time series leads to estimation of turning points in the history of the time series. These turning points can be compared with reference turning points to obtain insight into the lead/lag structure of an business indicator. The use of the nonparametric regression method requires the choice of a smoothing parameter. A "plug-in" method is used in the article. With this algorithm in the Ifo Business Climate, the same cycles as in the reference series of industrial production can be identified.

Analysts are particularly interested in the actual situation at the right bound-

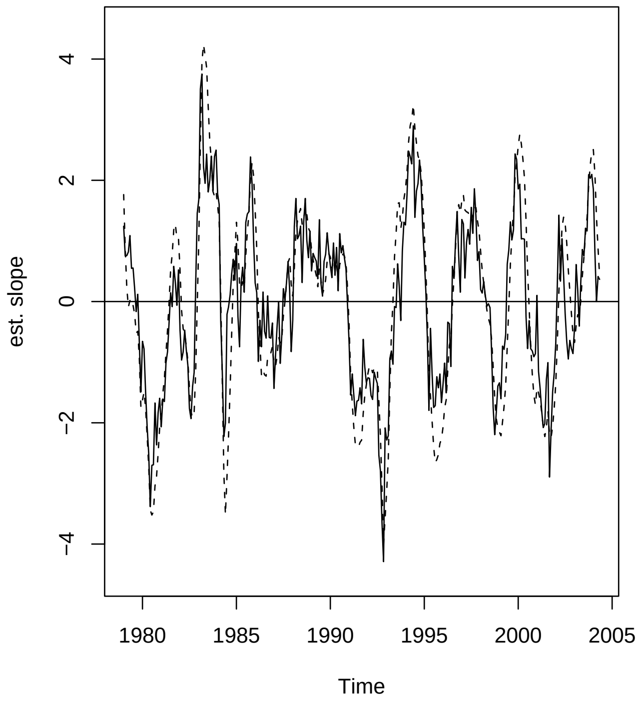

Figure 6: Structural time series estimated slope (solid line) and rolling non-parametric slope with plug-in bandwidth (dotted line) for the Ifo Business Climate

ary of the time series. In the article two data-based bandwidth selection methods are use for this purpose. The "plug-in" rule developed for estimating the whole function of slopes can also be used for estimating the slope at the boundary. Another bandwidth selector which is applied uses only information about the sign of the previously estimated slopes. Both methods lead to slightly different results. Comparison of the calculations shows that there is a trade off between early detection of a turning point and minimizing the amount of false signals.

A comparison of the nonparametric method with hidden Markov models and width structural time series methods does not lead to any clear winner regarding the early discovery of change points. The general course is recognized with all three methods. However, nonparametric results are those which are at least scattered. Since the nonparametric method is simply to calculate and presupposes only a few assumptions, it seems to be a suitable additional method for change-point analysis, although it cannot dominate the other procedures. In practice it is necessary to include the results of different methods in the decision-making therefore.

At least one should keep in mind that the above leads and lags of the business indicator are calculated ex post when the turning points of the real series are known. Not only that the values of the real series are published with a delay, it must also be decided whether in the actual situation a turning point occurs or not. So even when the business indicator shows a lag in the above tables this could be a lead in reality.

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