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Qualitative Business Surveys in Manufacturing and Industrial Production – What can be Learned from Industry Branch Results?

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Abstract

Business tendency surveys are a popular tool for the timely assessment of the business cycle, used by economists and by the public. This article considers survey results in the manufacturing sector in more detail and looks into the question of, whether the analysis of branch results leads to an information gain. The business cycle turning points are identified in the filtered series and average leads to the turning point of industrial production are calculated. In addition to these leads the ratios of the signal variances to the noise variances are calculated to assess the clarity of the signal contained in the indicator series. Apart from assessing the general business cycle course the survey results in manufacturing are often used to forecast moment-to-moment changes of industrial production. Analyses based on wavelets show that the survey balances are useful to forecast the larger scale movements only. Nevertheless, the comparison of out-of-sample forecast errors show that the inclusion of survey results as independent variables in an autoregressive model improves the forecasts.

JEL Code: C42, C22, E32.
Keywords: Business tendency surveys, business cycle analysis, turning points, Grnager causality, wavelet cross-correlations.

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1 Introduction

Business cycle analysts are permanently seeking (leading) indicators for the assessment of the state of the economy. Among others, business tendency surveys are a well established instrument for this assessment. These surveys usually use questionnaires with mainly qualitative questions, which are sent to a panel of firms. In Germany the Ifo Institute is specialized in business tendency surveys. The surveys are carried out monthly in Germany in the sectors manufacturing, construction, retailing, wholesaling and services.

This article uses the survey results from manufacturing only and analyses these results in detail. The question arises, whether the results from some specific branches in manufacturing are especially suited to assessing the state of the economy, and more specifically the performance of the manufacturing sector. The composite indicator for the sector is usually aggregated from the branch results with weights dependent on the value added of each of the branches. Thus, it might be argued that only those branches with high value added are important that also have a high weight in the overall index and thus an analysis at the branch level does not lead to additional insights. But this need not be the case. There could be branches that have a relatively small value added but that lead the business cycle. Also, the larger branches need not be synchronized over the business cycle. Clearly, every business cycle has its own characteristics and is different from the other cycles, but nevertheless, there could be branches that usually or quite often lead the overall business cycle.

Whether a time series is leading another one can be analyzed in various ways. In business cycle monitoring, the early identification of a turning point in the cycle is especially important. Therefore, this article seeks to establish, whether in specific branches the turning points are often signaled in a more timely way than in the composite time series. In addition, for the assessment of the current economic situation a valuable indicator should be relatively smooth to be reliable. Since smoothing methods are very sensitive at the borders of time series, good indicators should signal the turning points early and, in addition, the time series should contain only little noise. Another interesting question is whether the indicators are also suitable for forecasting the moment-to-moment movements of the target series. This quality is usually analyzed with the help of autoregressive models. In this article both characteristics the turing point analysis and the forecasts of moment-to-moment movements are analyzed at the branch level for the manufacturing sector.

Ifo' s most observed survey-based indicator for the German economy is the so-called Ifo Business Climate. It relies on two questions about the unspecified term "business situation". The first of the two questions focuses on the assessment of the current business situation with the possible answers "good", "usual", "bad". The second question is about the expected business situation in the coming six months with the predetermined answers "improve", "remain approximately the same", "worsen". For the business climate, the average of the net balances for both questions is calculated.

In the literature there is some discussion on how to quantify qualitative survey data. This point shall not be considered here, though. A common way to publish such data is the calculation of balances. This means that from the fraction of positive answers, the fraction of negative answers is subtracted. Nardo (2003) provides a survey about quantification of qualitative expectations. Öller (1990) finds balance statistics useful as a means for cyclical turning points, whereas Entorf (1993) and Cunningham et al. (1998) find that the use of balance statistic results in a loss of information. Since the publication of balances is a well established procedure, we use them in the following, keeping in mind that there might be room for improvements, using more elaborate quantification strategies.

GDP is usually used to assess the state of the economy. But since GDP data is usually available only quarterly, it is a common procedure to use production as a monthly reference for the economy or, even more appropriate, for the assessment of the manufacturing sector, which is an important cycle maker. We focus on the manufacturing sector only and use the monthly production time series as reference.

But this procedure raises another question: Why not use the survey results on a question about production expectations? In Ifo's questionnaire a specific question about the expectations on production for the coming three months is included. So we could consider whether this specific question is better suited to assess and to forecast production than the unspecific question about the business situation.

From the above discussion emerge four questions, which will be pursued in the following:

1. Are there branches that are especially suited to obtain early signals about the general economic course?
2. To assess the economic situation according to the production index, is it better to use the results of a specific survey question about production expectations or is also a more vague question about the economic situation useful?
3. How large are the ratios of signal variance to noise variance for the various indicators?
4. Are the branch results also useful for forecasting moment-to-moment changes of the production index?

In Section 2 the branch results are analyzed with regard to their ability to signal turning points in the reference series. The lead relations of the branch results for the different questions are considered. Section 3 contains the results of moment-to-moment forecasts. Autoregressive models for the first differences of the production series are estimated. These models include the survey balances as independent variable. To assess the performance of the models out-of-sample forecast errors are used. All findings are summarized in the last section.

2 Turning Point Analysis

To analyze the suitability of the business tendency survey results for the detection of turning points in the business cycle, these points have to be dated first. There are various dating procedures, and even more fundamentally, there are various definitions of business cycles. From the kind of questions in the survey and since the survey results contain no clear trend, it seems suitable to analyze growth (or deviation) cycles. This is a common procedure in the scientific literature, although in everyday practice the survey results are often compared with year-on-year growth rate cycles of the reference time series. Growth rates are asymmetric filters and have the advantage that they do not change when new observations are added to the time series. Asymmetric filters, on the other hand, lead to a phase shift of the time series and hence also shift the turning points.

There are a number of approaches in the literature for ascertaining turning points. These can be broadly classified as parametric or non-parametric. For the latter class, no formal statistical model of the series being dated is used to affect the dating. In contrast, there are methods which proceed by first fitting a statistical model to the data and then utilize the estimated parameters of that model to come up with some turning point dates. In this article a simple nonparametric method is used for the dating of deviation cycle turning points. Since this article aims at the comparison of turning point dates in a set of time series, it is reasonable to use a simple and robust dating procedure that can be used in the same way for all considered time series. For a discussion about the advantages and disadvantages of the dating procedures, see Harding and Pagan (2002) and Hamilton (2002).

The cycles in a series y_t can be expressed in terms of its turning points, which are local maxima and minima in its sample path. The simple dating rule of Bry and Boschnan (1971) is used. The rule is

$$ETS_t = \{(y_t > 0) \cap (\bigcap_{j=1}^{5} \Delta_j y_{t+j} < 0)\} \tag{1}$$

$$RTS_t = \{(y_t < 0) \cap (\bigcap_{j=1}^{5} \Delta_j y_{t+j} > 0)\} \quad (2)$$

where $\Delta_j = 1 - L^j$ and L the usual lag operator and ETS stands for expansion terminating sequence and RTS means recession terminating sequence. See also Artis et al. (2003) for a discussion of this method.

Before the dating algorithm is applied the time series are filtered with Hodrick-Prescott filters. Both a long-term trend and short-term fluctuations are removed from the series. The filter used by Hodrick and Prescott (1997) is actually a spline. The signal at time t, μ_t, is defined as the minimizer of the penalized least square criterion

$$\text{argmin}_{\mu_t} \sum_{t=1}^{T}(y_t - \mu_t)^2 + \lambda \sum_{t=2}^{T}((\mu_{t+1} - \mu_t) - (\mu_t - \mu_{t-1}))^2, \quad (3)$$

with λ the so called smoothness parameter which penalizes for roughness of the estimate. With $\lambda = 0$ the result of the minimization would be the interpolation of the data. As usual in spline estimation the smoothness parameter has to be chosen. One way to do this would be to use a data driven procedure, which for example tries to minimize a criterion like the mean integrated squared error. This approach is very popular in nonparametric regression estimation. Another approach, which is often chosen in business cycle analysis, is the use of the Hodrick-Prescott filter as a bandpass filter. The frequency response function w_{HP} of the filter is

$$w_{HP}(e^{-iw}) = \frac{1}{1 + 4\lambda(1 - \cos w)^2}, \quad (4)$$

with frequency w. The implicit cut-off frequency is the value w_c corresponding to the gain $|w_{HP}(e^{-iw})| = 1/2$. This satisfies the equation

$$\lambda = [4(1 - \cos w_c)^2]^{-1}. \quad (5)$$

The behavior of the filter enforces its interpretation as a low-pass filter.

In this article the filter is used to extract the business cycle information from the investigated time series. Therefore cycles with a period of more than 8 years are considered as trend component and removed from the series. On the other hand, components with periods shorter than 1.25 years are also considered as not business cycle relevant and are also removed from the series. Figure 1 shows the cyclical component of the industrial production index which results from the smoothing procedure. Also shown is the filtered time series of the Ifo Business Climate for manufacturing.

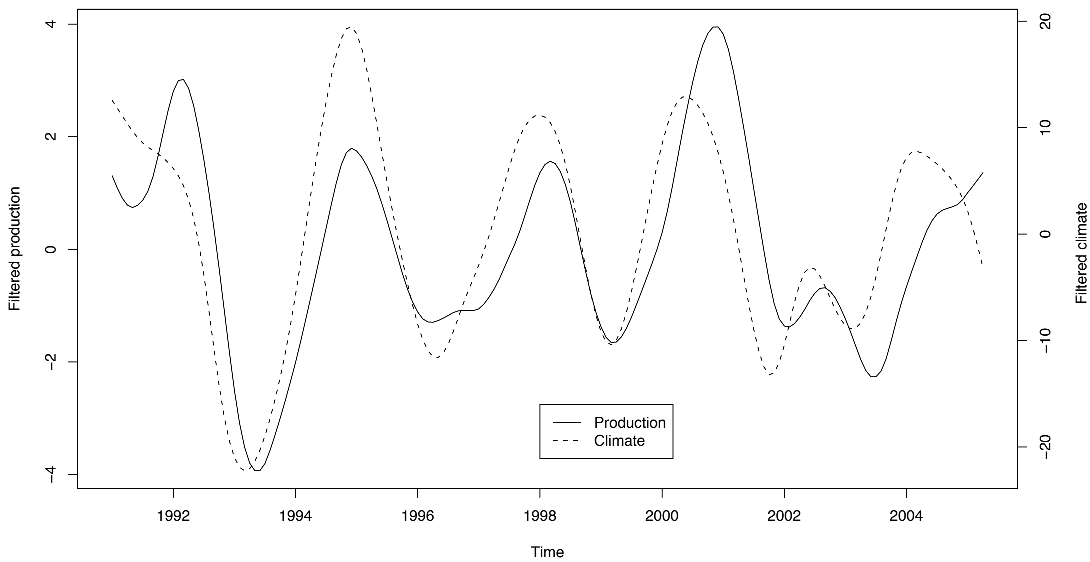

Figure 1: Bandpass filtered production index and Ifo Business Climate in manufacturing (from January 1991 until April 2005)

The Business Climate is an average of balances on two questions. In the first question the respondents can assess their current business situation as good/usual/bad. The second question focuses on the expectations for the next six months. The firms can assess their future business situation as improve/ remain apporoximately the same/ worsen. The interpretation of the term business situation is left to the respondents. In addition, the questionnaire send to the firms contains some more precise questions. Questions which are relevant in the context of the aim of this article are the one about the current stock of orders with response categories above normal/ normal for the season/ below normal and the one about the expected production over the next three month, which can be answered with increase/ remain unchanged/ decrease. In the following the above-described smoothing procedure is also applied to the results of these questions and the dates of the turning points are noted.

Table 1: Turning Points of the Production Index (S/N=4.41353)

		Turning Points of Production Index							
Peak		12.94		3.98		12.00		9.02	
Trough	6.93		4.96		3.99		2.02		6.03

Table 1 contains the dates of the identified turning points in the reference series of filtered industrial production which are used for the comparison with the survey results. There is a minor cycle in 2002 with a trough in February 2002. But September 2002 is not a peak when definition (1) is used because the value of the series at that time was not positive as it is required for the definition of a peak. It is indeed not a peak in the business cycle, because the production index remained under its long-term trend. Nevertheless, this cycle is treated like an ordinary one because the results of the business tendency surveys should also indicate such minor cycles. The ratio of the variance of the filtered production index, which is the business cycle signal, and the variance of the removed high frequency components with periods shorter than 1.25 years, which is the noise, is denoted by S/N. The larger the ratio, the more clearly is the business cycle component visible in the time series. For the industrial production index a signal to noise ratio of 4.41353 results.

Table 2 contains the leads in the respective turning points for the aggregated business climate in manufacturing as a whole and for the business climates in the various components of manufacturing. There are three rows for each indicator. The first row contains the leads in the peaks and in parentheses the average and the standard deviation of these leads; the second row contains the leads in the troughs and also the averages and the standard deviations of these leads (in parentheses) ;and the third row contains the S/N value [in squared brackets].

Several of the questions arised in the introduction can now be addressed. The aggre-

Table 2: Turning Point Analysis: Leads of the indicator series in the peaks (first row), in the troughs (second row) and signal-to-noise ratios (third row in squared brackets). The means and the standard deviations of the leads are in parentheses: (mean/standard deviation). A missing turning point is indicated by a "-" and an additional turning point is denoted by the date of its occurrence.

Indicator	Business Climate	Business Expectations	Production Expectations	Stock of Orders Assessment
Manufacturing	0, 2, 6, 3 (2.75/2.5)	3, 4, 9, 3 (4.75/2.87)	1, 3, 7, 3 (3.5/2.52)	-2, 1, 3, -5 (-0.75/3.5)
	3, -1, 0, 4, 4 (2.0/2.35)	5, 2, 2, 5, 3 (3.4/1.52)	5, 0, 1, 5, 3 (2.8/2.28)	1, -2, -1, -1, 1 (-0.4/1.34)
	[23.0229]	[10.25611]	[9.600818]	[45.93517]
Manufacturing without Food, Beverages, Tabacco	0, 2, 6, 3 (2.75/2.5)	2, 4, 9, 3 (4.5/3.11)	1, 3, 6, 3 (3.25/2.06)	-2, 0, 3, -4 (-0.75/2.99)
	3, -1, 0, 4, 4 (2.0/2.35)	5, 2, 2, 5, 3 (3.4/1.52)	5, 1, 1, 4, 2 (2.6/1.82)	0, -2, -1, 1, 0 (-0.4/1.14)
	[24.62488]	[11.21586]	[9.391706]	[45.62463]
Chemicals	1, 5, 9, 3 (4.5/3.42)	7, 16, 12, 3 (9.5/5.69)	6, 10.96, 1, 9, 3 (4.75/3.5)	0, 6, 3, -1 (2.0/3.16)
	2, 2, 2, 5, 3 (2.8/1.30)	5, 7, 4, 6, 3 (5.0/1.58)	3, 7, 8.97, 3, 8, 3 (4.8/2.49)	1, -1, 0, 1, 0 (0.2/0.84)
	[6.985407]	[2.834870]	[1.510018]	[6.755332]
Electrical and Optical Equipment	-1, 4, 5, 2 (2.5/2.65)	1, 5, 8, 2 (4.0/3.16)	1, 5, 6, 1 (3.25/2.63)	-4, 2, 1, 4, - (0.75/3.40)
	2, -1, 0, 3, 0 (0.8/1.64)	4, 1, 3, 5, 3 (3.2/1.48)	3, 0, 3, 4, 3 (2.6/1.52)	1, -3, -1, -2, - (-1.25/1.71)
	[13.30794]	[7.987943]	[5.999979]	[12.23572]
Transport Equipment	1, 3, 3, 2 (2.25/0.96)	4, -1, 3, 3 (2.25/2.22)	0, -1, 3, 3 (1.25/2.06)	-3, -2, 1, -5 (-2.25/2.5)
	2, -1, -1, 4, 2 (1.2/2.17)	6, 3, -1, 5, 3 (3.2/2.68)	5, -1, -1, 4, 1 (1.6/2.79)	0, -3, -7, 2, -6 (-2.8/3.84)
	[8.889362]	[3.799712]	[2.142327]	[11.44683]
Non-metallic Mineral Products	1, 1, 9, 3 (3.5/3.79)	3, -3, 9, 4 (3.25/4.92)	2, -, 9, 3 (4.67/3.79)	1, 1, 4, - (2.0/1.73)
	3, 2, 3, 4, 6 (3.6/1.52)	4, 3, 2, 6, 5 (4.0/1.58)	4, 2, -, 4, 0 (2.5/1.91)	5, -1, 4, -7, - (0.25/5.5)
	[5.939518]	[2.259669]	[0.8429785]	[2.217752]
Rubber and Plastic Products	0, 1, 5, 3 (2.25/2.22)	3, 2, 6, 3 (3.5/1.73)	2, -1, 7, - (2.67/4.04)	-1, 1, 6, - (2.0/3.61)
	3, 0, 0, 4, 4 (2.2/2.05)	5, 3, 1, 5, 3 (3.4/1.67)	5, 1, 0, 4, - (2.5/2.38)	1, 0, 0, 3, - (1.0/1.41)
	[14.72656]	[5.666372]	[4.265564]	[12.70234]
Metal Products	0, -2, 3, 3 (1.0/2.45)	2, 0, 8, 4 (3.5/3.42)	0, -2, 4, 3 (1.25/2.75)	-2, -3, 1, - (-1.33/2.08)
	3, -2, -2, 4, 5 (1.6/3.61)	5, 2, -1, 5, 5 (3.2/2.68)	6, 0, -1, 4, 6 (3.0/3.32)	-2, -2, -3, -1, - (-2.0/0.82)
	[11.23218]	[5.513115]	[4.112793]	[12.80698]
Furniture, Music Instruments, Sporting Equipment	1, 2, 6, 3 (3.0/2.16)	3, 2, 7, 4 (4.0/2.16)	1, 2, 5, 3 (2.75/1.71)	1, 9.96, -3, 6, - (1.33/4.05)
	4, 3, 1, 3, 5 (3.2/1.48)	5, 2, 2, 5, 5 (3.8/1.64)	4, 1, 4, 2, 5 (3.2/1.64)	10, 3, 6.97, 1, -10, - (2.0/8.29)
	[4.733709]	[2.267250]	[1.535608]	[3.630816]
Wood and Wood Products	2, 2, 6, 5 (3.75/2.06)	3, 8.96, -3, 8, 4 (3.0/4.55)	2, 8.96, -3, 4, 5 (2.00/3.56)	0, 7, 13, 6 (6.5/5.32)
	6, 3, 1, 4, 4 (3.6/1.82)	5, 6, 10.97, 1, 4, 2 (3.6/2.07)	10, 6, 1.97, -8, 3, 7 (3.6/6.95)	6, 1, 3, 6, 5 (4.2/2.17)
	[5.044254]	[1.544827]	[0.8591979]	[4.751214]
Machinery and Equipment	0, -1, 6, 3 (2.0/3.16)	1, 4, 9, 3 (4.25/3.40)	1, 3, 7, 3 (3.5/2.52)	-4, -1, 1, 2 (-0.5/2.65)
	3, -1, 0, 4, 3 (1.8/2.17)	5, 1, 2, 6, 3 (3.4/2.07)	5, -1, 1, 4, 2 (2.2/2.39)	0, -9, -3, -1, 1 (-2.4/3.97)
	[20.22914]	[10.88707]	[10.40658]	[27.83561]
Metals and Fabricated Metal Products	0, 4, 8, -2 (2.5/4.43)	2, 7, 12, 3 (6.0/4.55)	3, 15, 11, 4 (8.25/5.74)	-1, 4, 6, -2 (1.75/3.86)
	2, 0, 2, 4, -1 (1.4/1.95)	6, 5, 4, 9, 1 (5.0/2.92)	6, 4, 4, 9, 1 (4.8/2.95)	-2, -1, 2, 2, -3 (-0.4/2.30)
	[19.32461]	[8.986936]	[2.318806]	[21.04025]
Refined Petroleum Products	5, 6, -2, 3 (3.0/3.56)	4, 13, 19, 4 (10.0/7.35)	-12, 6, 3, 4 (0.25/8.26)	-5, -5, 1, -9 (-4.5/4.12)
	7, 9, -3, 2, 6 (4.2/4.76)	0, -2, 11, 5, 4 (3.6/5.03)	-6, -8, 0, 6, 1 (-1.4/5.64)	-8, -1, -3, 1, -5 (-3.2/3.49)
	[1.342312]	[0.599599]	[0.4136748]	[0.4105644]
Paper, Publishing and Printing	0, 1, 6, 4 (2.75/2.75)	1, 3, 8, 3 (3.75/2.99)	1, 3, 7, 3 (3.5/2.51)	0, 1, 7, 8 (4.0/4.08)
	4, 0, 1, 4, 5 (2.8/2.17)	5, 1, 2, 4, 5 (3.4/1.82)	3, 1, 1, 4, 3 (2.4/1.34)	2, 1, 2, 5, 4 (2.8/1.64)
	[14.85938]	[4.924024]	[3.6604]	[16.99477]
Textiles	9, 6, 5, 2 (5.5/2.89)	9, 8, 9, 2 (7.0/3.37)	8, 13, 9, 1 (5.25/4.99)	11, -1, 6, 2 (4.5/5.20)
	10, 0, -2, 1, 5 (2.8/4.76)	9, 1, 0, 3, 3 (3.2/3.49)	10, 2, 0, 2, 4 (3.6/3.85)	12, 2, -1, 1, 5 (3.8/5.07)
	[5.399861]	[2.443655]	[1.584084]	[2.295845]

gated business climate in manufacturing signals the turning point on average with a lead and in addition the S/N value is equal to 23.0229, indicating that the signal in the business climate is much stronger than in the production index. Using the business expectations alone as an indicator arises the average leads but with a reduced S/N. The signal in the production expectations is almost as strong as in the business expectations but with a shorter lead. A strong signal results from the question about the assessment of the order stock, but this indicator does not lead the reference series. Overall, there is a tendency that peaks are signaled with a larger lead than troughs. On the other hand, the standard deviations of the leads seem to be smaller in the troughs.

When the food sector is not included into the aggregation, the results are almost unchanged. A separate analysis of the food industry shows that it tends to extra cycles and that its signal to noise ratio is very small with S/N=1.437961. Therefore this part of the industry is not considered further in the following turning point analysis at the branch level.

In Germany, the branches that contribute a high value added are machinery, electrical and optical equipment, metal products, transport equipment and, with a little less value added, chemistry. Table 2 can be used to identify branches that give often or on average earlier turning point signals than the overall indicator. Chemistry is one branch that gives very early signals. The S/N is lower than that of manufacturing, though. Electrical equipment does not lead the manufacturing results, on average. It is remarkable, that in this branch the question about the current stock of orders does not have a much larger S/N compared to the other questions that gave earlier signals. In transport equipment the production expectations are a relatively bad indicator and assessment of the current stock of orders is clearly lagging. Also for non-metallic mineral products the production expectations do not give as good results as the business climate, which seems to be a good indicator for the troughs. Both the mean lead and the standard deviation are appealing for the troughs. Rubber and plastic products and metal products have reasonable S/N ratios but do not, on average, signal turning points earlier than the overall indicator. The S/N values in furniture and wood are not very high; in comparison, machinery has appealing S/N values but does not lead the overall indicator. Metals and fabricated products also show interesting S/N ratios and leads on average the aggregated manufacturing indicator, although the lead is quite variable, especially in the peaks. Paper does not lead the overall results and textiles has relatively low S/N values (but not smaller than the ratio in the production index itself), but there is a strong lead in the peaks.

The above discussion shows that especially metals and fabricated metal products and chemistry are branches that tend to lead the overall indicators. This is convincing, because in both branches and also in the branches textiles, which shows a lead in the peaks, and non-metallic mineral products, which is appealing in the troughs, important intermediate goods are produced. The results in the table also suggest that at least in Germany the vague questions about the current and the expected business situation leads to reasonable results in all branches. The more concrete questions about current stock of orders and production expectations deliver mixed results. This is a very interesting result because the questions about the business situations can also be used in surveys in the non-manufacturing sectors like retailing or services. The usefulness of these questions in other sectors is not considered in this article, however.

3 Autoregressive Analysis

The previous section analyzed the filtered time series and considered the detection of turning points in the business cycle. Now the moment-to-moment changes of industrial production are considered. The first differences of the production index is now the target series. A common procedure to assess the usefulness of an indicator consists of two steps. First, an autoregressive model is estimated for the target series and then in the second step the indicator is included as a regressor in the autoregressive model for the target series. When the inclusion of the indicator improves the forecasts of the purely autoregressive model, then the indicator is assessed as useful. But this procedures also has its weaknesses. Differencing causes a phase shift in the time series and in addition inflates the high frequency components of the time series. The month-to-month changes are also very sensitive to seasonal effects and extraordinary large orders. Compared to this behavior the qualitative business tendency survey is constructed in such a way that it gives quite robust signals about the economic course. Especially because of the qualitative nature, extraordinarily large orders cannot have a strong effect. A good business cycle indicator should be not be very volatile, because the signals should be visible as clearly as possible. Nevertheless, the indicator should be helpful for predicting moment-to-moment changes of the industrial production series.

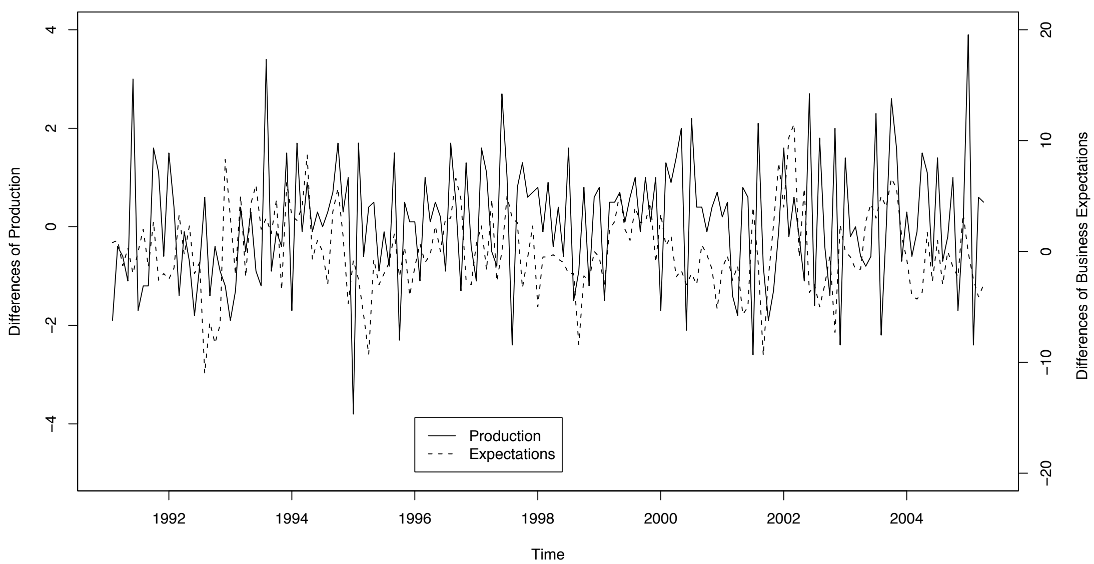

Figure 2: Differences of industrial production and differences of Ifo Business Expectations for manufacturing (from February 1991 until April 2005)

Figure 2 shows the first differences of industrial production along with first differences of the business expectations of the manufacturers. There are business cycles visible in the series of first differences but also the high volatility of the series is striking. Since differencing the production index causes a phase shift of the time series, the indicator series are also differenced to maintain their qualities as leading indicators. To visualize these characteristics, wavelet cross-correlations can be calculated. With the help of wavelets a time series $f(t)$ can be decomposed as follows:

$$f(t) = S_J + D_{J-1} + ... + D_j + ...D_1. \tag{6}$$

Where S_J denotes cycles with periodicity greater than 2^{J+1} (say the ̈trend ̈) and the D_j components capture cycles between 2^j and 2^{j+1}.

The decomposition of time series on a scale-by-scale basis offers the ability to unveil structures at different time horizons. This decomposition may be generalized to multivariate time series. The wavelet cross-covariance and the wavelet cross-correlation between two time series is a decomposition of the linear dependency on a scale-by-scale basis, thereby making it possible to see how the association between two time series changes as a function of time horizon. An introduction to these topics is included in the book of Gencay et al. (2002). Whitcher et al. (2000) investigate the wavelet cross-covariance for specific types of nonstationary processes, and Serroukh and Walden (2000) discuss wavelet cross-covariance of stationary processes including long-memory processes.

Although wavelets can have infinitely different shapes, all wavelets share some basic construction plan. Depending on the normalization rules, there are two types of wavelets within a given family: father and mother wavelets. For father wavelets

$$\int \Phi(t)dt = 1, \qquad \text{with} \quad \Phi_{j,k} = 2^{-\frac{j}{2}}\Phi\left(\frac{t-2^jk}{2^j}\right) \tag{7}$$

and, for mother wavelets

$$\int \Psi(t)dt = 0, \qquad \text{with} \quad \Psi_{j,k} = 2^{-\frac{j}{2}}\Psi\left(\frac{t-2^jk}{2^j}\right), \tag{8}$$

for $k \in \{1, 2, 3, ..., N\}$ and $j \in \{1, 2, 3, ..., J\}$. $\{\lambda_j\} = 2^{j-1}$, $j \in \{1, 2, ..., J\}$ is the socalled scaling factor and J denotes the maximum scale. Father wavelets are used for the trend components and mother wavelets are used for all deviations from trend. The representation of a signal $f(t)$ now can be given by

$$f(t) = \sum_k s_{J,k}\Phi_{J,k}(t) + \sum_j \sum_k d_{j,k}\Psi_{j,k}(t). \tag{9}$$

For the purpose of this article, the socalled maximal overlap discrete wavelet transform (MODWT) is used. See Percival and Walden (2000) for a detailed description of various wavelet approaches. Using the MODWT coefficients an estimator of wavelet covariance and wavelet correlation can be calculated.

Figure 3 shows the wavelet cross-correlations between the first differences of the production index and the business expectations. Since J=3 is chosen, the figure in the last row shows the correlations of the trend component with cycles of periods larger than $23 + 1 = 16$ months. At this scale there are significant cross-correlations visible. This is in contrast to shorter time scales where the correlations are very low and not significant. This pattern indicates that the two time series share a similar business cycle component, but that the short-term fluctuations are not very similar. This result is comprehensible because the aim of the qualitative business surveys is, as already discussed, the measurement of the business cycle. Short-term effects which are contained in the quantitative measure of production are not captured by the qualitative survey. But the wavelet cross-correlations also point to another important fact. The peak of the cross-correlations of the S_3 components is at about -2. This negative value indicates that the business expectations are lagging. The reason for this unpleasant result is caused by the differencing of the production time series. This differencing leads to an pronounced phase shift of the time series and causes the lagging behavior of the expectations. Therefore an appropriate procedure is the use of differences of the business expectations as indicator. This differencing causes a phase shift also in the indicator series and re-establishes the properties of the expectations as leading indicator. This can be verified in Figure 4. These graphs show the wavelet cross-correlations between the first differences of the production index and the first differences of the business expectation in manufacturing. Again there are only very low correlations at the shorter scales, which are not significant. Only for the S_3 components are the correlations significant and this time they indicate that the business expectations are a leading indicator.

That the first differences of the business expectations are a useful indicator for the business cycle relevant movement of the first differences of industrial production can also be confirmed with the help of Granger causality tests. To do this we follow a common routine and estimate bivariate VAR models with lag lengths chosen by the BIC information criteria. Table 3 contains the p-values of the F-Test for Granger causality. Thereby y denotes the target series of differenced industrial production and x denotes the differenced business expectations. The arrows indicate the direction of the causality under test. The causality is tested separately for the different time scales of the wavelet decomposition. For the shortest scale $d1$ the p-values do not indicate a causal relationship in either direction. For the larger scales the test statistics indicate significant causalities of the indicator variable at reasonable levels of significance. The results, in addition, are very robust against the choice of the lag length of the VAR model.

Table 3: p Values for Granger causality tests

	d1	d2	d3	s3
$x \rightarrow y$	0.4961235	0.02463875	0.0003373863	0.02799122
$x \leftarrow y$	0.5640555	0.59560876	0.1331389107	0.15247974

The Granger causality test indicates significant relationships even for the D_2 and D_3 scales where the wavelet cross-correlations found no remarkable correlations. The above results confirm that the business expectations are a useful indicator for the movements of the first differnces of industrial production only when the expectations are also differenced and even then they are only helpful for the larger scale movements of the target series. The short term movements are not very well reflected in the qualitative survey results. This is not a disadvantages of the qualitative surveys; in contrast it is one of its important strengths, because they are not as strongly influenced as the quantitative measures by outliers, and by singular effects. But it is important to remind these characteristics when the forecast performance of qualitative surveys is considered. The above calculations are presented only for the business expectations at the aggregated level. But similar conclusions are valid when the other survey questions, which are analyzed in Section 2 of this article, are considered and when the results are analyzed at the branch level.

Although the scale-by-scale analysis showed that the differences of the survey balances are an indicator for the medium- or longer-term components rather than for the short-term movements of the differences of industrial production, it would be interesting to see whether the indicators are useful for the forecasting of the overall movements of the differenced industrial production series. A common procedure to analyze this issue consists of a two step procedure. First a purely autoregressive model of the target variable is estimated and used for the calculation of point forecasts. These forecasts are compared with that of an autoregressive model, which also contains lags of the indicator variable as regressors. In the present study we focus only on one-step prediction errors but calculate real out-of-sample forecasts. Table 4 contains the mean squared prediction errors of rolling out-of-sample forecasts. To compute the forecast errors the first 42 observations are used only to estimate the model. The AIC is used to choose a purely autoregressive model and respectively an autoregressive model which contains lagged indicator variables. With the estimated model a one-step out of sample forecast is calculated. Then the next observation is included in the sample and a model is chosen and estimated to calculate the next one-step forecast error and so on, rolling until the end of the time series.

The MSPE without any indicator as independent variable is about 1.397. Including the aggregated results of the survey question for manufacturing leads for all four indicators to an improvement in the error measure. The p-values in the brackets below the error measure for the manufacturing indicators show that all error reductions are significant. The test procedure behind these p-values is the modified Diebold and Mariano test, as described in Harvey et al. (1997). This test is intended to test the

Table 4: MSPE with first differences of survey time series as predictor

Indicator	Business Climate	Business Expectations	Production Expectations	Stock of Orders Assessment
without independent	1.396589			
Manufacturing	1.188212	1.227824	1.161966	1.150508
	(0.003292)	(0.009199)	(0.005624)	(0.001469)
Manufacturing without Food, Beverage, Tabacco	1.181206	1.243197	1.221616	1.135421
Chemicals	1.26478	1.327783	1.300899	1.275152
Electrical and Optical Equipment	1.251022	1.311926	1.218702	1.220654
Food, Beverage, Tobacco	1.260593	1.29001	1.141079	1.333808
Transport Equipment	1.277267	1.327886	1.360181	1.167846
Non-metallic Mineral Products	1.151390	1.149429	1.255536	1.238104
Rubber and Plastic Products	1.179975	1.183568	1.184779	1.321540
Metal Products	1.191901	1.207078	1.282391	1.252641
Furniture, Music Instruments and Sporting Equipment	1.163829	1.195027	1.174938	1.362675
Wood and Wood Products	1.202856	1.257426	1.289204	1.350713
Machinery and Equipment	1.164767	1.232429	1.149742	1.309844
Metals and Fabricated Metal Products	1.181303	1.189150	1.268960	1.337031
Refined Petroleum Products	1.168365	1.315319	1.379224	1.391274
Paper, Publishing and Printing	1.299434	1.329623	1.275612	1.256149
Textiles	1.278002	1.296140	1.343303	1.300643
Combination	1.111442	1.134711	1.127705	1.2002336
Combination without food	1.109890	1.138497	1.143736	1.198009

equality of mean squared prediction errors. Also the prediction errors which results for the four different questions can be compared in pairs. The resulting p-values are contained in Table 5 and indicate no rejection of the null hypotheses that the forecast performance of the models is equally good.

Table 5: p values of modified Diebold/Mariano test for the comparison of forecast errors

	Business Climate	Business Expectations	Production Expectations	Stock of Orders Assessment
Business Climate	-	0.2449743	0.3638287	0.2672664
Business Expectations		-	0.1718918	0.1726288
Production Expectations			-	0.4427674
Stock of Orders				-

Compared with the results for the aggregated indicators there are no clear improvements when the indicators at the branch levels are used. In most of the cases the forecast performance worsened and only in a few cases is the MSPE reduced slightly. These improvements are not significant, though. Browsing the branch results a tendency that often the inclusion of the business climate gives the best results is striking. Remarkable although also not significant improvements can be obtained when the average of the individual branch level forecasts are used as forecasts. The results for these average forecasts are shown in the last two rows of Table 4. Especially for the business climate and the business expectations the MSPE can be reduced. So averaging different forecasts might be a strategy that leads to improved forecasts.

Overall the analyses of this section show that the results of business tendency surveys are also useful for the prediction of moment-to-moment changes of industrial production, at least for the larger scales of the target series. However, there is no type of question which clearly is the best and there is also no strong evidence that some branches are especially suited to forecast these changes. The reason for these indistinct results might be that the survey balances are not very suitable for the prediction of the short scale component of differenced industrial production.

4 Conclusions

The main idea of this article was to analyze the usefulness of branch results of business tendency surveys for the assessment and the prediction of the business cycle in manufacturing. Although every business cycle is different, there are indeed some branch results which tend, on average, to give earlier signals than the aggregated results. But this lead has its price. The strength of the business cycle signal measured by the signal-to-noise ratio of the indicators is lower than in the aggregated indicator. Another question of interest is whether the Ifo-typical weak question about the business situation is suitable for the analysis or whether it would be better to ask a precise question about production. The results show that both types of questions have their value. The strengths of the weak question about the business situation is that it gives reasonable results over all branches and that the signal-to-noise ratios are very favourable. Experience at Ifo shows that these questions even work well in other sectors of the economy like retailing where the business cycle should be measured on the basis of other variables than production.

The above messages are only valid when the general business cycle course is considered. The picture is different when the target series are the moment-to-moment changes of the production index. Analyses based on wavelet decompositions show that the qualitative survey results are only useful for forecasting the larger scale movements of the changes of the industrial production index. The small scale movements of the series are not connected. So the survey balances seem to be not very suitable for the prediction of the short scale component of differenced industrial production. But this might be a strength and not a weakness of the business tendency survey approach.

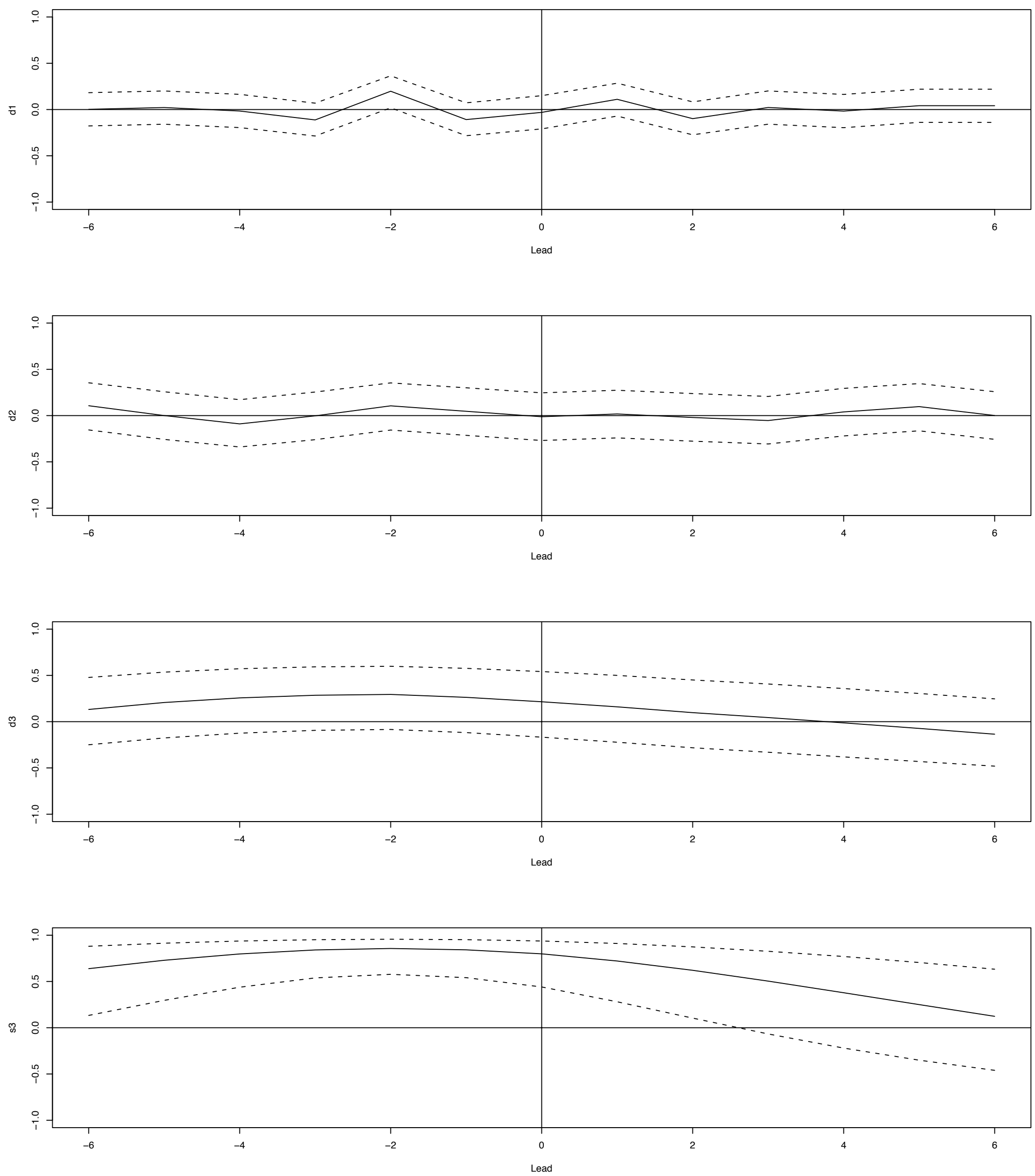

Figure 3: Wavelet cross-correlations between differences of industrial production and Ifo Business Expectations for manufacturing (from February 1991 until April 2005)

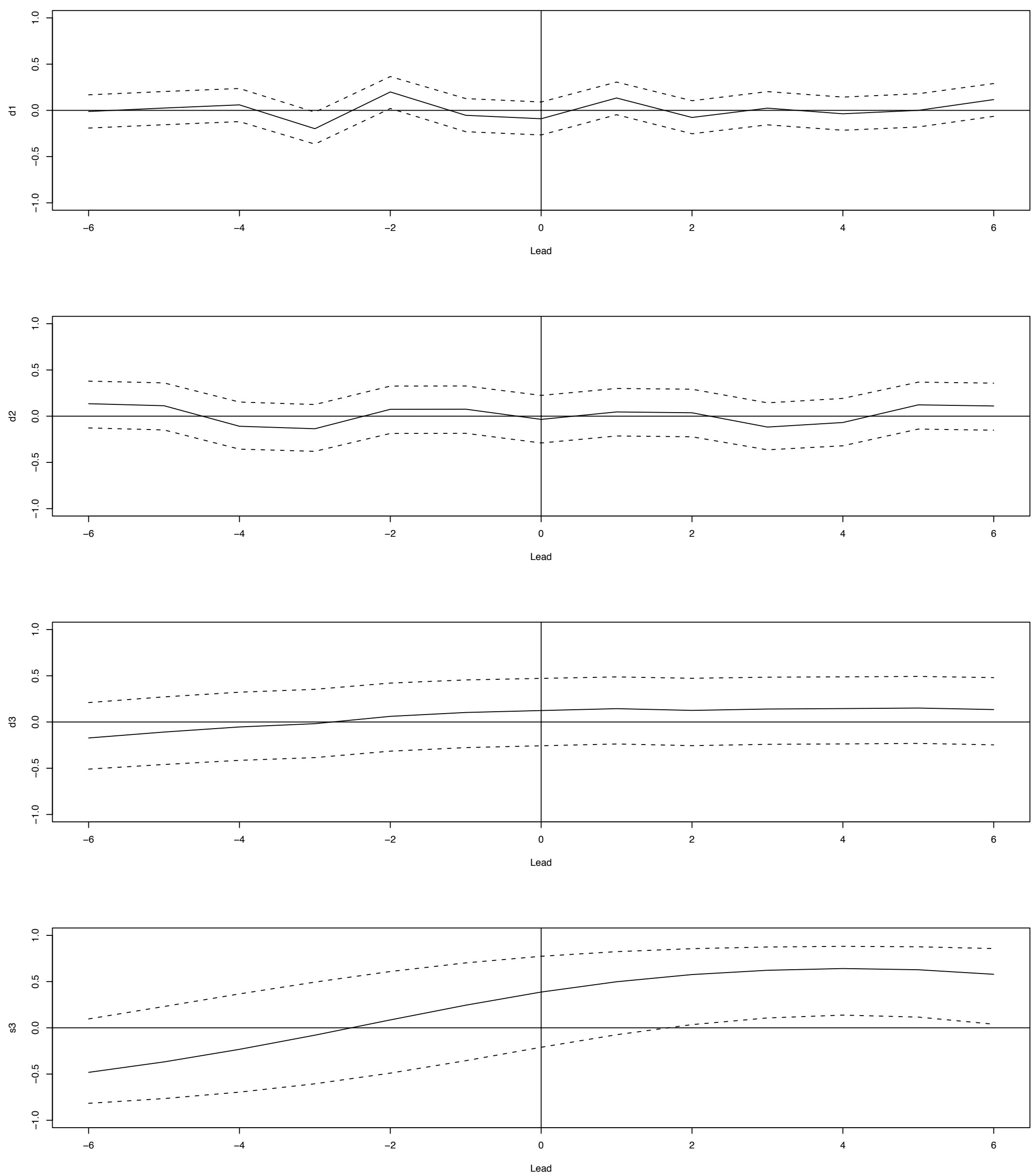

Figure 4: Wavelet cross-correlations between differences of industrial production and differences of Ifo Business Expectations for manufacturing (from February 1991 until April 2005)

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