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SECTORAL LEVEL AND RESPONSES IN
NON-BALANCED FORM**

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Anticipatory Survey Data in Leading Indicators:
Gains from Using Data at Sectoral Level and Responses in Non-Balanced Form¹

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Abstract: This paper suggests improvements on leading indicators based on survey data. Three main points are discussed. a) The use of survey data at sectoral level results in a longer lead of the indicator series. Exploiting the information contained in "no change" answers by applying the concept of "canonical coherence" and by running regressions on certain wave-lengths lead to higher cross-spectral coherencies between the indicator and the reference time series. b) Lead-lag relationships calculated from the frequency domain are compared with results of the time domain, thereby highlighting potential superpositions of seasonal and business cycles. c) "Out of sample" forecasts, finally, reveal an inferior performance of the traditional balance concept. It is dominated by a weighed average of "worse" and "equal" responses, and also by the application of the simple "worse" share. Surprisingly, the latter is even the overall dominating alternative.

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1. Introduction

Survey data play a prominent role in leading indicators of business cycles. A well-known example is the "Composite Leading Index" of the Organization for Economic Co-Operation and Development (OECD). Its German index contains nine components, four of which come from the Ifo-Konjunkturttest, i.e. the business survey of the Information und Forschung (Ifo) Institut für Wirtschaftsforschung ("Information and Research" Institute for Economic Research, Munich). Using Ifo data, we intend to demonstrate that survey data contain even more information than generally used in indicators up to now.

Whether forecasting methods with disaggregate data lead to better results than those with highly aggregate data has not been agreed upon. As Makridakis (1986) points out, the lower the level of aggregation the higher the level of randomness might be, which in fact is an argument supporting simple methods and aggregate time series. However, an important aspect of leading indicators is also to provide time series with maximal leads. Forecasts which rely on these data are, of course, not as accurate as forecasts which are, say, one or two months ahead. Early indicators can be used in addition to more stable indicators to obtain both types of time series in a composite system of indicators. Potential gains are to be expected from the observation that some industrial sectors lead while other sectors lag. For instance, Klein and Moore (1983) identify consumer goods and materials in leading positions. More recently, Entorf (1991a,b) confirms the lead of consumer goods industries by means of cross-spectral analysis and vector autoregression. In Section 2 of this paper, we will show that sectoral leads also exist for survey data which implies a longer lead when compared to the aggregation of all sectors.

Another aspect of disaggregation addresses the key question of how to efficiently implement information of micro-survey data. A typical business survey question offers three alternative responses: "better" (or "increase"), "equal" (or "no change") and "worse" (or "decrease"). The most common way of representing aggregate information is by constructing balances, i.e. the difference between the shares of "better" and "worse" answers. For the analysis of cross sections, there are many papers available which stress the potential loss of information inherent in such a procedure (see, for instance, Nerlove and Press, 1976, and König, Nerlove and Oudiz, 1981, for early applications of appropriate microeconomic techniques and Ronning, 1990, as well as Low, McIntosh and Schiantarelli, 1990, for recent surveys).

The methods proposed in these studies are of limited relevance for determining indicator *time series* which may help prepare economic policymaking or entrepreneurial decisions. The literature on how to use the different categories in indicator time series is hardly developed. Teräsvirta (1986) is an exception: he illustrates that separating "better" and "worse" as different variables is a promising way of making short-term forecasts. Teräsvirta, however, still ignores the information within the "no change" category, which is far from being a realization of a Gaussian white noise process. Recently, a paper by Öller (1990) reveals that the "no change" category reveals more relevant information than the "better" responses. Applying quarterly data of the time period 1976 to 1987 of the Finnish forest industry, his best forecasting model uses a logit transformation of "equal" and "worse" responses, whereas the alternative introduction of optimistic responses does not improve the forecasting accuracy.

In fact, analyzing German Ifo cross-section data, Ronning (1986, 1990) shows that the categories "no change" and "increase" may reflect similar economic situations, since the two variables reveal a strong positive correlation. To cope with the problem and to obtain an aggregate measure of all categories, the probably best known way is the quantification technique in the tradition of Theil (1952) and Carlson and Parkin (1975, see Ivaldi, 1990, for a critical appraisal and a comparison with other quantification techniques). This approach requires assumptions on the correct distribution of the latent survey variable to estimate the limits of the no change interval. It is assumed that the latent survey variable has the same distribution as the corresponding actual realization, which might be justified in case of inflation and inflationary expectation, but which, however, bears a problem when the survey variable concerns the general "economic situation". Here, no corresponding bench-mark exists.

These qualifications reveal the straightforward requirements an indicator using all different categories must meet: The components have to be combined in such a manner that the new leading indicator has a maximal coherence with the corresponding reference time series, for instance, with industrial production and/or GNP. The statistical concept of canonical correlations fits almost perfectly in the profile demanded, with one important exception: The correct lead of the indicator has to be known in advance. However, the analysis of turning points provides a somewhat artificial tool to deal with the problem, whereas regression methods - as the most popular alternative - can be seriously affected by seasonal phenomena. Barsky and Miron (1989) have shown that seasonal variation accounts, for instance, for more than 85 percent of the fluctuations in growth rate of the U.S. real GNP. Hence, even with seasonally adjusted data the calculation of the correct lead could be biased, since seasonal filtering reduces the variance of the time series by such a considerable amount.

Thus, we first use the frequency domain to construct a "canonical" indicator. A linear combination producing the maximal (canonical) coherence with a coinciding indicator of business cycles, the index of industrial production, is presented. Due to the nature of spectral estimation, the estimate of the lead is not affected by seasonal distortions. Whereas regression analysis is affected by all frequencies, spectral analysis allows us to disentangle seasonal variations from business cycle frequencies, which are, by definition, of major interest in forecasting business cycle phenomena.

The special attention given to seasonality helps in understanding alternative time domain results. Highlighting seasonal lead-lag relationships, we discuss the lead-lag structure emerging from a cross-correlation analysis.

Actual forecasts are made in the time domain. Thus, we check the performance of the balance concept for realistic "out of sample" forecasts. Applying a recent method proposed by Fair and Shiller (1989,1990), we compare the traditional balance with a weighted balance of "equal" and "worse" responses and with the "pure and simple" share of "worse" responses.

This paper is organized as follows. After a short description of the data in Section 2, Section 3 presents estimates for the leads of sectoral survey data as well as estimates for the corresponding reliabilities of these measures. Section 4 describes the performance of the canonical indicator compared to the balance concept. In Section 5, we link preceding results from the frequency domain to subsequent time domain investigations by comparing lead-lag relationships of both approaches. "Out of sample" forecasts are presented in Section 6. Section 7 draws conclusions and suggests areas of future research.

2. The data.

The survey data used in this work originate from the business survey of the Ifo Institute and cover monthly observations from 1960(1) to 1989(12). From the regular questionnaire we single out the responses to the question on the *expected business condition* (see the Appendix A1 for the question appearing in the questionnaire). The data are applied both in disaggregate and balanced form. "Disaggregate" means using variables T^+ , T^- , T^0 , Y^+ etc., where the superscript denotes that the variables - representing data of a particular sector - are relative shares of "better" (+), "equal" (=) or "worse" (-) responses. Balances are defined and calculated as, for instance, $T^b = T^+ - T^-$. The Ifo *expected business condition* is commonly assumed to reflect future (expected) demand (cf. König and Nerlove, 1986, Nerlove, 1983), making it particularly suitable as a leading indicator.²

As the reference time series representing the business cycle, we use the coinciding indicator (see, for instance, Klein and Moore, 1983, for a classification of indicators) *index of real industrial production* of the Statistisches Bundesamt (German Statistical Office), also available for the time period 1960(1) - 1989(12). To allow comparisons with recognized leading indicators, we introduce the already mentioned *composite leading index* of the OECD (available for 1962(1) - 1989(12)) and the *business climate* (1960(1) - 1989(12)) of the Ifo Institute.³

3. The identification of leading sectors using survey data.

To identify sectors with a long lead of the survey variable *expected business condition*, we proceed with the following two sequential steps: a) we check whether a time series has a peak in the business cycle frequency domain, and b), if this is true, we include the variable in a cross-spectral analysis to estimate the lead at business cycle frequencies.

Table 1 summarizes the first step. To detect the exact duration of long waves, it is necessary to detrend the time series. Otherwise, all spectra would reveal the typical "Granger shape" of economic spectra, i.e. a strongly decreasing functional form with a peak at the zero frequency. We apply the simple first differences filter which avoids disadvantages such as artificial cycles,

² Also Öller (1990), after testing the performance of six selected survey questions, finds the related Finnish survey variable "business outlook" as being most suitable for forecasting the business cycle.

³ Based on Ifo balances, the climate variable is calculated as the geometric mean of the *evaluation of the present business condition* and the *expected business condition*. Averaging both questions leads, of course, to a shorter lead when compared to the expectation but also to a more reliable forecast.

spurious causalities etc. arising from time regression (see Nelson and Plosser, 1982 and Nelson and Kang, 1981, 1984). Because of its simplicity, the effects of filtering can be identified easily. The spectrum is multiplied by a monotonic increasing function over the whole range of frequencies (Priestley, 1981, p. 599). Thus, the filter has a transparent influence which avoids artificial phenomena such as Yule-Slutsky effects.

According to a rule of thumb, the ratio of the number of autocovariances and the number of observations, M/N , should range between $1/3$ and $1/5$. 1960(1)-1989(12) implies a maximum of 360 observations from which we choose $M=90$. 97 spectral points are estimated within each spectrum. Hence, the identification of cycles at $\lambda=2 \times 96/j$, $j=0,1,2,\dots,96$ is possible. For low frequencies, this choice allows a discrimination between ∞ (=trend), 192, 96, 64, 48, 38.4, 32, ..., 12, ... months.

For the analysis of lead-lag relationships of sectoral *expected business conditions*, Table 1 contains sectors which have been identified as leading in a former investigation of actual production data. According to cross-spectral estimates in Entorf (1991b), we select the textile sector (which has the longest lead in Entorf, 1991b), motor cars (second position), toys (fourth position), chemicals (median position) as well as the main industry groups consumer durables, consumer nondurables, investment goods and basic industries. The analysis also covers the aggregate, i.e. total industry. In our initial steps, we use the traditional concept of balances.

Table 1 summarizes all cycles lasting longer than twelve months. With two exceptions, the data reveal cycles with a duration between three and four years, which are widely accepted as business cycles. Existing peaks representing cycles between 19 and 24 months are much smaller than those of business cycles. They cannot be interpreted easily. Most probably, they represent harmonics of longer cycles. For instance, a fundamental business cycle of 48 months is characterized by harmonics at $\lambda=j/48$, $j=1,2,\dots,24$, i.e. at frequencies of 24, 16, 12, 9.6, ... and 2 months. Seasonal variations (12 months) are, of course, only detectable for nonadjusted series. It is interesting to note that despite the particular form of the question, where respondents are asked to disregard seasonal fluctuations (cf. Appendix A1), also the time series *expected business condition* shows significant signs of seasonality (which is a result already presented by König and Nerlove (1985), and which can also be found in case of Finnish survey data (Öller, 1990, p. 457)).

After eliminating chemicals and motor cars, all remaining variables have business cycles with roughly the same duration such that cross-spectral estimates can be interpreted in a reasonable way. In particular, if coherencies are high, phase spectra provide a reliable base for calculating

lead-lag relationships. Table 2 illustrates the delay of industrial production behind the survey based indicators.⁴ Results are presented for both identified business cycles, i.e. 48 and 38.4 months, as well as for the seasonal cycle. The figures confirm previous results which were derived using actual production data instead of survey questions. As in Klein and Moore (1983) and Entorf (1991a,b), we observe a lag of investment industries and a lead of consumer goods industries. To be precise, consumer nondurables have a longer lead than consumer durables which does not come as a surprise because of the difficult delimitation of consumer durables from investment goods. For the two-digit industries being considered, we observe a lead of about 12-14 months for the textile industry, whereas the relatively short lead for toys (second position in Entorf, 1991b) is an exception to the results confirmed by actual production data.

It is interesting to note that the data on expectations lag *behind* the production index at the seasonal cycle (the only exception is OECD, where the result is insignificant because of seasonal adjustment). These lags most probably bias lead-lag relationships arising from regression and cross-correlation downward, since these methods are based on all frequencies. The problem will be considered in Section 5. As expected for spectral methods and for our simple filter, seasonality does not seriously affect the estimation in the frequency domain. We observe almost the same results for the seasonally adjusted index. This is particularly true for leads with high coherencies. The coherence function between two series is interpreted as the correlation coefficient by frequency. Hence, it helps to judge the reliability of estimated leads. The footnote of Table 2 reveals that with exception of consumer nondurables coherencies are highly significantly different from zero. In this sense, the *business climate* and the OECD *composite leading index* are the most reliable indicators. However, their estimated leads (which correspond to figures published by the OECD, 1987, p.121) are significantly smaller than the one of the *expected business condition*, in particular when compared to the textile sector. Moreover, the results for the OECD cannot be seriously compared with the Ifo data since the OECD makes subsequent corrections after first presenting a preliminary index.⁵

⁴ Confer also Öller, 1990, for the spectral estimation of phase leads of survey variables at business cycle frequencies. This study's time period of 48 observations, however, which is rather short for a spectral time series analysis, limits more profound conclusions concerning particular frequencies, for instance, of selected business cycles.

⁵ Five weeks after the base period, the OECD publishes a preliminary index with only 40 percent of all necessary indicators available (OECD 1987, p.40). The *expected business condition* is published two weeks after the base period without subsequent corrections (Nerb, 1982, p.78).

Summing up, Table 2 reveals improved leads when compared to the *business climate* and the *OECD composite index*. The high quality of the *expected business condition* can be seen in the lead of 9-11 months of total industry but also in the high corresponding coherencies which range between 0.78 and 0.83. Moreover, the coherence function has absolute maxima at the 48-month frequency which underlines the quality of estimated lead-lag relationships at that frequency. This maximum also exists for the textile sector. The long lead of the textile industry is the earliest indicator of future business cycle activities. Since coherencies are satisfactorily high, the survey questions of this sector will be subsequently used for the construction of a canonical indicator.

4. The determination of "canonical" indicators

When the relative share of "no change" responses is neglected, information is lost as a consequence. A simple descriptive indication of this problem can be seen in the correlation between the "=" shares and the remaining categories. For the total industry between 1960(1)-1989(12), we observe a correlation 0.34 between "+" and "=" and -0.83 for the correlation between "-" and "=" . The latter is even higher than the expected negative one between "+" and "-", which turns out to be -.77. The same pattern applies to data at sectoral level. In addition to the literature mentioned in the introduction, these figures might suffice to demonstrate that "no change" responses contain important information.

Analogous to the concept of canonical correlation, the concept of canonical coherencies produces for two sets of variables $(x_1, x_2, \dots, x_n)$ and $(y_1, y_2, \dots, y_m)$ the parameters $\alpha_i (i=1, 2, \dots, n)$ and $\beta_j (j=1, 2, \dots, m)$ such that for a particular frequency under consideration the coherence between the linear combination $z = \sum \alpha_i x_i$ and $w = \sum \beta_j y_j$ is maximized. For instance, this methodology enables us to construct a linear combination of indicators which guarantees a maximal coherence with a linear combination of coinciding indicators. For the purpose of highlighting potential gains from using the "no change" category, we reduce the linear combination of coinciding indicators to the single time series *index of industrial production*. Since we limit the case to $m=1$, we can interpret our approach as a multiple regression in the frequency domain. For this particular case, Hannan (1970, p.258) shows that the coherence function is of the form⁶

⁶ Hannan (1970, p.258) called this coherence emerging from multiple regression "multiple coherence".

$$(1) \quad C_{xy} = f_y^{-1} f_{yx} f_x^{-1} f_{xy}$$

and the parameter vector of the linear combination emerges as

$$(2) \quad \alpha = f_x^{-1} f_{xy}$$

Here f_y represents the spectrum of industrial production. Furthermore, considering the general case of indicators X^+ , $X^=$, X^- (any relative shares) that arise from the categories "+", "=", and "-", we need the following vectors and matrices of estimated spectra and cross spectra:

$$(3) \quad f_x = \begin{pmatrix} f_{x^+} & f_{x^+=} & f_{x^+=-} \\ f_{x^+=x^+} & f_{x^+=} & f_{x^+=-} \\ f_{x^+=x^+} & f_{x^+=} & f_{x^+=-} \end{pmatrix}, \quad f_{xy} = \begin{pmatrix} f_{x^+y} \\ f_{x^+=y} \\ f_{x^+=y} \end{pmatrix}$$

For the practical procedure, we consider the 48-month business cycle. Before the calculation of equations (1) and (2) can be performed, we have to estimate the lead of the indicators such that the production index will be related to the exactly corresponding predictors. However, our results reveal that the leads of "+", "=", and "-" do not coincide. Hence, in order to provide a "canonical" indicator $X_{t-\tau}^*$ that gathers the available information within the "better", "equal" and "worse" responses such that $X_{t-\tau}^*$ guarantees a maximal coherence with the current index of industrial production Y_t , we first have to determine τ , the point of time where all information is available. Then, after estimating the leads of the "+", "=", and "-" responses, which we define as τ_1 , τ_2 and τ_3 respectively, we can reformulate our maximizing problem as follows: Determine α_1 , α_2 and α_3 such that

$$(4) \quad X_{t-\tau}^* = \alpha_1 X_{t-\tau_1}^+ + \alpha_2 X_{t-\tau_2}^= + \alpha_3 X_{t-\tau_3}^-$$

$\tau = \min(\tau_1, \tau_2, \tau_3)$, has a maximal coherence with the index of industrial production Y_t .

Table 3 presents the canonical indicator for total industry and for the textile sector. We use seasonally adjusted data for Y_t (the results are quite similar for non-adjusted data and the conclusions are the same). The linear combinations reveal that the "+" variable has the longest lead, whereas the "=" share lags and hence determines the month in which all information is available. Our results confirm that neglecting the "no change" category is not justified: in both cases the parameter of the "=" category is the *largest* one. Compared to the balance

concept, coherencies increase from 0.83 to 0.86 for total industry and from 0.77 to 0.81 for textiles. Inspecting Table 2 gives an idea of the degree of improvement: a difference of about 0.03-0.04 roughly corresponds to the difference between the *expected business condition* (total industry) and the *business climate*. However, for the better performance of the latter one, it was necessary to use *extraneous* information arising from the question on the firms' *present business condition*.

5. Comparing cross-correlation and cross-spectral estimates.

So far, the investigation focuses on lead-lag relationships exclusively based on frequency domain estimations. It is interesting to study potential deviations of these spectral results from a traditional cross-correlation analysis, which is affected by *all* frequencies. With the same variables as for the cross-spectral estimation in Table 2, Table 4 presents estimates of maximal cross-correlations $r(y_t, x_{t-\tau})$, $\tau \geq 0$, between the seasonally adjusted index of industrial production, y , and corresponding anticipation variables, x . The non-stationarity is accounted for by calculating seasonal growth rates, $z_t := \log(Z_t) - \log(Z_{t-12})$, $Z=Y, X$.

Again, the most reliable indicator is the *composite index* of the OECD (leads of five and six months produce the identical maximum), followed by the Ifo *business climate* and the total industry *expected business condition*. When compared to the spectral results of Table 2, the corresponding leads of the maximal cross-correlation results are closer to the leads of the 38.4-months frequency (also included in Table 4). Hence, a first conclusion would be that the shorter duration is the more relevant estimate for the average cycle (both durations, 48 and 38.4 months, were estimated for univariate spectra, cf. Table 1).

Alternatively, the superposition of seasonal and business cycles, both being present in survey data, could possibly explain the decreased lead at the 48-months cycle: Table 2 reveals a simultaneous *lag* of the Ifo variables at the seasonal frequency and a *lead* at business cycle frequencies. The last column of Table 4 presents the spectral "net lead" of both cycles. For these corrected estimates, cross-spectral estimates and cross-correlations do coincide

surprisingly well. For coherencies larger than 0.80 (cf. Table 4), results are even identical (for business climate, total industry, investment goods the leads are 4 and 4.1, 9 and 8.5, 7 and 7.0, respectively).⁷

Only the lead of 17 months of consumer nondurables is strange at a first glance, however, in this case we have to be aware of the general relationship between phase leads at business cycles and cross-correlations (see Appendix A2). Here, the relevant maximal correlation is -0.496, which is the minimum of all *lags*, realized at a lag of 10 months. Considering a 38.4-months cycle, a lag of 10 months associated with a negative correlation is equivalent to a lead of $38.4/2-10=9.2$ months with positive correlation (cf. Appendix A2). Hence, when compared to the "pure" lead at the 38.4-months frequency, there remains a difference between 11.8 and 9.2, but this sector's business cycle coherence is low anyway (cf. Table 2).⁸

Comparing the survey results to those of *actual* production data, we find more evidence of leading consumer goods industries: Even more evident than in the frequency domain, we observe a lead of consumer nondurables and a lag of investment goods (relative to the average, total industry). At a more disaggregate level, also the long lead of toys (besides textile) is confirmed (as for actual production in Entorf, 1991b).

Generally, leads and lags of survey expectations are inconsistent with rational market assumptions. Since the questionnaire's general form of the "business condition" question captures the firm's current general business cycle expectation, we may conclude that firms, even sectors, do not have complete information and identical information sets. According to the informational lead-lag structure, information propagates from consuming to supplying sectors.

⁷Of course, conclusions concerning the superposition of seasonal and business cycles are only tentative. Detailed evidence can be gained by some Monte Carlo simulations of realistic situations. For instance, leads and lags are more important close to their turning points, where the contribution to the overall variances is much higher than in "normal" (average) situations. Hence, results for business cycles with long and flat upswings differ from those with symmetric cycles. Thus, investigations have to take into account more realistic asymmetries of both business cycles and seasonal cycles. However, such an analysis is beside the point here and we leave it for future work.

⁸In terms of the "net lead" at the 48-months cycle, the corresponding results are 10.1 and $48/2-10=14$, respectively.

6. A comparison of "out of sample" forecasts.

6.1. The forecasting procedure

We will examine the question whether the usual way of using balances is justified in terms of forecasting business cycle activities, measured as the *index of industrial production*. Since we are primarily concerned with forecasting the business cycle, we eliminate trend components by applying the Hodrick-Prescott filter to the logarithms of all time series.⁹ This approach produces stationary quarterly data¹⁰ such that forecasting the trend is not necessary.¹¹

In all cases, our forecasting equation has the identical simple form

$$(5) \quad {}_T\hat{y}_{T+\tau} = \hat{\gamma}_T I_T^*,$$

where T is the time when the forecast is made, ${}_T\hat{y}_{T+\tau}$ is the forecast τ months ahead and I_T^* represents the information set available at time T . Here, the latter will be replaced by our trend corrected survey based indicators, which remain to be specified below. Due to the identical form, a comparison between alternative forecasts is only affected by data, not by the individual specification.

Forecasts are made "out of sample", i.e. we use data up to a final period T , estimate the regression

$$(6) \quad y_t = \gamma_T I_{t-\tau}^* + u_t,$$

where the observation period is $t=1964(1), \dots, T$, and we substitute the estimated coefficient $\hat{\gamma}_T$ into the forecasting equation (5).

Moreover, we calculate *rolling* regressions and forecasts. The beginning observation is held fixed at 1964(1) and the sample expands by one observation each time a time period elapses.

⁹ In this approach, the trend component tr_t is the one that minimizes

$$\sum_{t=1}^T (y_t - tr_t)^2 + \lambda \sum_{t=2}^{T-1} ((tr_{t+1} - tr_t) - (tr_t - tr_{t-1}))^2,$$

where we choose $\lambda=1600$ in accordance to the theory of real business cycles (cf. Kydland and Prescott, 1990)

¹⁰ Computational applications of the Hodrick-Prescott filter require quarterly or annual frequencies such that we average monthly observations.

¹¹ Of course, as generally assumed for business cycle filtering, we have to know the trend component in advance.

The initial endpoint of this regression procedure is $T=1978(1)$ (so the first forecast concerns $1978(1)+\tau$), the final sample period ends with $T=1989(4)-\tau$ (such that the final forecast is made in $1989(4)-\tau$ for $1989(4)$).

The competing forecasts are compared in different ways. Firstly, we calculate "root mean squared errors" (RMSEs)¹² and correlation coefficients between forecasts and forecasted series. Since RMSEs and correlations only insufficiently discriminate between alternative forecasts, we apply secondly a procedure proposed by Fair and Shiller (1989,1990). It compares two different forecasts and tests whether one forecast contains relevant information completely dominating the information provided by the competing forecast.¹³

The practical application of the Fair-Shiller procedure is quite easy. Using the actual time series, y_t , and the two competing forecasts of this time series arising from the rolling regression procedure, $\hat{y}_t^1$ and $\hat{y}_t^2$, we estimate the following regression:

$$(7) \quad y_t - y_{t-\tau} = c + a(\hat{y}_{t-\tau}^1 - y_{t-\tau}) + b(\hat{y}_{t-\tau}^2 - y_{t-\tau}) + u_t,$$

which is corrected for autocorrelation in our subsequent application.

If one of the candidates produces redundant information, then the corresponding coefficient a or b will be nonzero, if both forecasts provide important and independent information, then both a and b should be nonzero and if neither of the competitors contains any useful information, both estimates should be zero.

The competing forecasts are selected as follows. We want to check the justification of balances. Hence, the first two candidates are trend corrected balances of total industry and textile industry, i.e. we replace I_t^* of equation (5) by y_t^i and t_t^s , respectively. Alternatively, we implement the survey shares of "better", "equal" and "worse" in an optimized way. Table 5 displays the leads of the different survey categories and the corresponding maximal cross-correlation coefficients with industrial output. The Hodrick-Prescott filtered time series confirm previous results: the lead of *expected business conditions* of total industry (balances) is three quarters, that of the textile sector five quarters (also measured in terms of the balance).

¹² We compute RMSEs according to

$$RMSE = 100 \sqrt{1/N \sum_{n=1}^N (\hat{y}_n - y_n)^2},$$

where N = number of forecasts.

¹³ The idea of the test is related to the literature on encompassing tests, as it is developed by Davidson and MacKinnon (1981), Hendry and Richard (1982), Mizon and Richard (1986) and others.

Moreover, we observe the highest correlation coefficients for the "worse" category and the lowest values for the "better" responses. We will use this lead structure and the evidently good performance of "equal" and "worse" in our forecasting regression, which is discussed below.

To guarantee a true *ex ante* character of the forecasting procedure, we calculate a weighted average of "equal" and "worse", which we call "equal-worse" balance. It is estimated using weights of the initial estimation period, i.e. the weights are fixed at the stage of 1978(1). Thus, the weights are the estimated parameters of the regression

$$(8) \quad y_t = \alpha y_{t-2}^- + \beta y_{t-3}^- + \epsilon_t, \quad t = 1964(3), \dots, 1978(1),$$

in case of total industry and

$$(9) \quad y_t = \alpha t_{t-4}^- + \beta t_{t-5}^- + v_t, \quad t = 1965(2), \dots, 1978(1),$$

in case of textile industry. Thus, when compared to the traditional balance concept, we neglect the information of the "better" category and replace it by the share of "equal" responses. The estimation results are (t-values in parentheses)

$$(10) \quad y_t = \underset{(2.2)}{0.091} y_{t-2}^- - \underset{(4.3)}{0.035} y_{t-3}^-,$$

and

$$(10) \quad y_t = \underset{(2.9)}{0.104} t_{t-4}^- - \underset{(3.6)}{0.031} t_{t-5}^-.$$

The estimated parameters of 1978 are then used to define I_t^* of the forecasting regression (5):

$$(11) \quad I_t^* \equiv 0.091 y_t^- - 0.035 y_{t-1}^-, \quad t = 1964(2), \dots, 1989(4),$$

for total industry and

$$(12) \quad I_t^* \equiv 0.104 t_t^- - 0.031 t_{t-1}^-, \quad t = 1964(2), \dots, 1989(4)$$

for textile industry. The introduction of invariant weights guarantee a fair comparison with the balance concept, where the weights (-1 and 1) are also fixed. In terms of the forecasting equations (5) and (6), the leads are two quarters for total industry and four quarters for textile industry. At these points of time, all information would be available.

Motivated by the high correlation between the "worse" category and the *index of industrial production*, our third alternative is the simple "worse" category of total and textile industry, respectively.¹⁴

6.2. The results.

Table 6 and Table 7 present the performance of the different leading indicators measured as RMSE, correlation between "out of sample" forecast and actual realization, and in terms of the Fair-Shiller procedure. According to the specification of lags in equations (8)-(11), the leads of the "equal-worse" balance are exactly specified as 2 for total industry and 4 in the case of textile industry. Hence, we compare the forecasts of these indicators with corresponding two-quarters-ahead and four-quarters-ahead forecasts based on balances and "worse" categories of total industry and textile industry, respectively. In addition, we check the lead of three quarters in case of total industry and the lead of five quarters for textile industry, both being the maxima of the cross-correlation functions of the balance time series.

The balance forecast is the worst of all alternatives. For total industry, the "equal-worse" balance has the highest correlation, and, surprisingly, the "worse" category has the best RMSE performance. Also for a lead of three quarters, RMSE and correlation of the balance are lower than those of the "worse" category.

The RMSE and the correlation estimates of the textile example reveal a much weaker performance, but again the correlation coefficients of the balance are the lowest and only the RMSE estimates of the balance are slightly better than the ones of the "worse" share.

The "Fair-Shiller competition" of Table 7 confirms the dominating role of the "worse" share. Direct comparisons show that the information of the "worse" category contains the information of the balance and even that of the "otimized" weighted "equal-worse" balance. For the lead of three quarters, the t-value of "worse" is only weakly significant, but in this case the information of the balance is completely irrelevant (t-value=0.1).

The Fair-Shiller regressions of the textile industry produce only one significant result, that is the dominance of the "equal-worse" balance over the traditional balance. All other t-values do not exhibit any relevant information contained in the indicators. This result is unexpected

¹⁴ Also in a canonical correlation analysis by Entorf (1991c), the "worse" categories of *expected business condition* and *evaluation of the present business condition* have the largest contributions to a *multivariate* leading index based on survey data.

when compared to the good performance of this sector in the frequency domain. As discussed in Entorf (1991c), a reason can be seen in a decreasing lead of the textile industry for the last part of the sample period.

Summing up, the dominance of the "worse" responses is a striking result, in particular, since it is also preferable to the "optimized" weighted indicator constructed from the "worse" and the "equal" categories.¹⁵ Due to potential overfitting, the higher R^2 in a regression framework does not guarantee a better performance in "out of sample" forecasting. Moreover, balances do not discriminate situations of 40% in the "better" regime and 50% in the "worse" regime from respective shares of 10% and 20%, for instance. Evidently, the signals occurring in the balance, -10 in either case, do not tell as much about the corresponding economic situation as the original numbers themselves.

7. Conclusions.

Survey data contain additional information usually ignored in existing leading indicators of the business cycle, which are mainly implemented in balanced form. Taking German survey data on expectations as an example, investigations in the frequency domain show that a) survey data at sectoral level can extend the lead of leading indicators and b) that using the information of the "no change" category improves the reliability of the indicator when compared to the traditional balance concept. Spectral methods reveal a lead of (nondurable) consumer goods and, at the two-digit industry level, a maximal lead of the textile sector. Coherencies can be increased by applying regression methods performed in the frequency domain and by implementing the information of the "no change" category.

The results of the frequency domain are compared to some time domain investigations. The phase leads at business-cycle frequencies are very close to cross-correlation results, in particular, when a potential superposition of business and seasonal cycles is taken into consideration.

Practical forecasts have to be performed in the time domain. Hence, by running realistic "out of sample" forecasts and by implementing the information contained in survey responses in alternative ways, we check whether the use of balances is justified. Surprisingly, the forecast

¹⁵ In a related paper, Entorf and Kavalakis (1991) show that the "worse" responses also dominate weighed averages of "better" and "worse" which is tested for lags of two, three and four quarters of total industry.

of the simple "worse" category turns out to be the "best"; it not only dominates the traditional balance concept but it is also preferable to a more sophisticated weighted average of "worse" and "equal" responses.

Forecasts based on regression might be distorted by seasonality. So far, we ignored potential shortcomings mainly arising from seasonal variability in survey responses or by possible seasonal maladjustment in official statistics. Future work should highlight interactions between seasonality, forecasting and canonical indicators.

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Appendix

A1) We base our data on a questionnaire, monthly distributed to 5000-6000 firms as part of the regular Ifo-Konjunkturtest (Ifo business survey). The question concerning the *expected business condition* is phrased:

I. Disregarding seasonal fluctuations, what business condition do you expect in the next 6 months with respect to the business cycle?

- positive
- satisfactory, or normal for the season
- negative

The following question asks for the *evaluation of the present business condition*:

II. How do you evaluate the present business condition?

- positive
- unchanged
- negative

To stabilize the erratic swings brought about by single questions, the Ifo Institute calculates the *business climate* as follows:

$$\text{Business climate} = \sqrt{(\text{present b. c.} + \text{cst.})(\text{expected b. c.} + \text{cst.})} - \text{cst.}$$

Since the *climate* makes use of balances, constants (200) have been added to avoid negative values.

A2) Exhibit 1 displays two time series x_t and y_t with a common 48-months business cycle. By inspecting this figure, we see that both time series are completely "in phase" (= perfect correlation +1.0) when we compare x_t with y_{t-20} and when we calculate $r(x_t, y_{t-20})$. The same lead-lag structure of both time series is characterized by a perfectly *negative* correlation between x_t and y_{t+4} , i.e. $r(x_t, y_{t+4}) = -1$.

Using the information of the sign of the co-spectrum, our used spectral estimation procedure identifies phase leads such that the correlation between x_t and $y_{t-\tau}$ (τ = phase lead) is positive. Hence, for a given business cycle of T periods and a computed lead of τ , it is always possible to calculate equivalent lags with negative correlation by applying the formula $\tau = T/2 - \tau$. Vice versa, using the same transformation, a lag τ with negative correlation corresponds to a lead $T/2 - \tau$ with positive correlation).

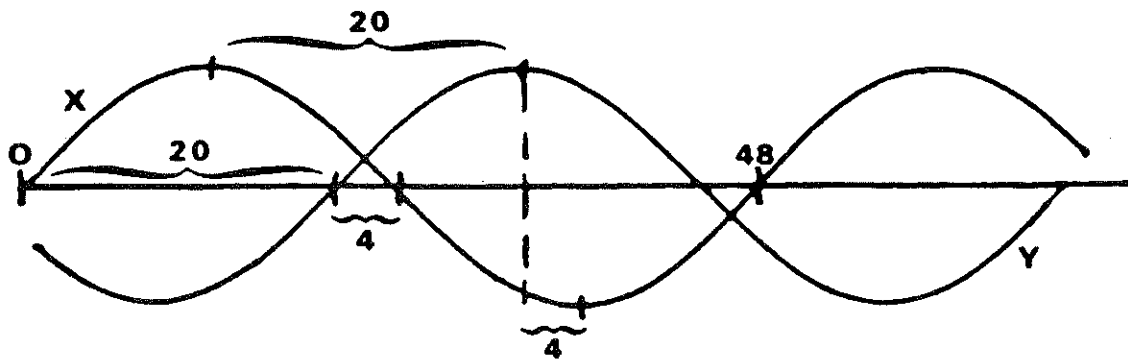


Exhibit 1: Cross-correlation and phase lead

Table 1

Spectral estimates: duration of cycles (in months)

Series ^a	Cycles ^b
Index of industrial production, 60-89	48, 21.3, 12
Index of industrial production, seasonally adjusted, 64-89	48, 21.3
Ifo business climate, 60-89	48, 21.3 (24), 12
OECD composite leading index, 62-89	48, 21.3
Ifo expected business condition (balances)	
- total industry, 60-89	38.4, 12
- consumer durables, 60-89	38.4 (48), 19.2, 12
- consumer nondurables, 60-89	38.4, 19.2, 12
- investment goods, 60-89	48, 12
- basic industries, 60-89	38.4, 21.3, 12
- motor cars, 60-89	27.4, 12
- chemicals, 66-89	32, 19.2, 12
- toys, 60-89	38.4 (48), 19.2, 12
- textile, 60-89	38.4 (48), 19.2, 12

Notes:

a) The time span refers to the estimation period (monthly data).

b) The figures represent corresponding peaks of the spectrum indicating cycles lasting longer than 12 months. Figures in parentheses denote that one cannot distinguish between both estimates by visual inspection of the spectral plot. The estimation implements a Parzen-type spectral window and covariances up to a lag of 90 months. The data are used in differenced form. 97 spectral points allow one to discriminate between frequencies at $2\pi 96/j$, $j=0,1,2,\dots,96$ months.

Table 2

Estimation of phase spectra: Lag of the German industrial production index^a and corresponding coherencies^b

Anticipation data	Lag of				
	non-adjusted index at frequency (months)			seasonally adjusted index at frequency (months)	
	48	38.4	12	48	38.4
Ifo business climate	6.7 (.87)**	5.7 (.81)	-2.6 (.65)*	7.1 (.89)**	5.8 (.85)
OECD composite leading index ^c	6.8 (.88)	5.7 (.82)	1.6 (.14)	6.9 (.90)	5.6 (.87)
Ifo expected business condition (balances)					
- total industry	10.8 (.83)**	9.0 (.78)	-2.3 (.68)*	11.1 (.83)**	8.9 (.79)
- consumer durables	10.4 (.75)*	8.9 (.68)	-2.6 (.57)*	10.8 (.77)*	8.7 (.70)
- consumer nondurables	13.2 (.45)	12.1 (.32)	-3.1 (.47)	13.6 (.50)	11.8 (.37)
- investment goods	9.4 (.85)**	8.0 (.75)	-2.4 (.70)*	9.6 (.83)**	7.8 (.75)
- basic industries	12.2 (.67)	9.7 (.66)	-1.9 (.68)*	12.4 (.69)	9.7 (.68)
- toys	9.5 (.68)*	8.4 (.67)	-2.2 (.69)*	10.2 (.71)	8.7 (.73)**
- textile industry	14.5 (.76)**	11.5 (.73)	-2.6 (.68)*	14.6 (.78)**	11.4 (.75)

a) The estimation period for the non-adjusted data is 1960(01)-1989(12) (T=360), for the seasonal adjusted series it is 1964(01)-1989(12) (T=312). The number of cross-covariances used is M=90 in the first and M=78 in the second case (such that M/T=1/4). The estimates are based on first differences. 97 spectral points are calculated (cf. Table 1)

b) Cross-spectral coherencies are given in parentheses. **) and *) denote respectively absolute and local maxima of the coherence function. Critical values are 0.34 (significance level = 0.01) and 0.22 (significance level = 0.05) (Jenkins and Watts, 1968, pp.379-81).

c) Cross-spectral estimates of the OECD data are based on the time period 1962(01)-1989(12) (T=336). 84 cross-covariances are used.

Table 3

Comparing canonical indicators and balances^a

Indicator	Corresponding realization of industrial production ^b	Coherence ^c
Total industry:		
$Y_t^+ = 0.269 Y_{t-4}^+ + 0.348 Y_t^- - 0.057 Y_{t-2}^-$	Y_{t+8}	0.860
$Y_t^+ - Y_t^-$ (balance)	Y_{t+11}	0.831
Textile industry:		
$T_t^+ = 0.260 T_{t-4}^+ + 0.421 T_t^- - 0.162 T_{t-2}^-$	Y_{t+12}	0.810
$T_t^+ - T_t^-$ (balance)	Y_{t+15}	0.773

Notes:

a) Estimation period: 1964(06)-1989(12)

b) Lead-lag relationships are estimated at the 48-months frequency.

c) The number of cross-covariances M is adapted such that $M/T=0.25$ in each case. For details of the estimation procedure, see Table 2.

Table 4

Cross-correlation functions: Lag of the German industrial production index, corresponding maximal correlations^a, and a comparison with estimated phase leads

Anticipation data	Maximal correlation	Lead of survey variable (months)	Lead at the 38.4-months business cycle ^b	"Net lead" at the 48-months business cycle ^c
Ifo business climate	0.684	4	5.8	4.1
OECD composite leading index	0.827	5,6	5.6	-
Ifo expected business condition (balances)				
- total industry	0.505	9	8.9	8.5
- consumer durables	0.457	9	8.7	7.8
- consumer nondurables ^d	0.473/-0.496	17/-10	11.8	10.1
- investment goods	0.475	7	7.8	7.0
- basic industries	0.486	9	9.7	10.3
- toys	0.472	11	8.7	7.3
- textile industry	0.438	15	11.4	11.9

Notes:

a) The estimation is based on seasonal growth rates of the time period 1965(01)-1989(12)

b) See Table 2 for the phase lead at the 38.4 cycle (seasonally adjusted index)

c) "Net lead" = (phase lead at the 48-months cycle, non-adjusted index) + (phase lead at the seasonal cycle); cf. Table 2 for the spectral estimation.

d) Cf. Appendix A2) for the relationship between correlation and spectral phase leads.

Table 5

Maximal cross-correlations between the *expected business condition* and the index of industrial production: results for deviations from trend

<i>Expected business condition of</i>		Lead (quarters)	Maximal cross- correlation (at indicated lead)
Sector	Category		
Total industry	"better"	3	0.484
	"equal"	2	0.564
	"worse"	3	-0.664
	balance	3	0.554
Textile industry	"better"	6	0.443
	"equal"	4	0.597
	"worse"	5	-0.617
	balance	5	0.579

Note:

The estimations are based on deviations from trend, using the Hodrick-Prescott decomposition into trend and cyclical component.

Table 6

"Root mean squared errors"/ correlation coefficients between actual data^a and forecasts^b

Sector	Lead	Balance	"Equal-worse" balance	"Worse" share
Total industry	2	1.93 / 0.48	1.86 / 0.57	1.80 / 0.56
	3	1.96 / 0.49	-	1.87 / 0.55
Textile industry	4	2.38 / 0.24	2.31 / 0.39	2.41 / 0.31
	5	2.35 / 0.32	-	2.36 / 0.37

Notes:

a) the (Hodrick-Prescott) trend-corrected index of industrial production.

b) see Section 6 for the calculation of forecasts.

Table 7
Results of the Fair-Shiller procedure.

Sector, lead (qrts.)	Parameters ^a and t-values of competing forecasts based on			AR(1)- parameter	DW- statistic	SEE
	Balance	"Equal-worse" balance	"Worse" share			
Total industry						
2	0.30 (1.4)	0.44* (2.0)	-	0.61 (4.6)	1.65	0.01331
	-0.67 (1.2)	-	1.39* (2.4)	0.58 (4.2)	1.78	0.01306
	-	0.34 (1.6)	0.50* (2.2)	0.64 (4.9)	1.69	0.01292
3	-0.05 (0.1)	-	0.70 (1.4)	0.67 (6.0)	1.51	0.01315
Textile industry						
4	0.22 (1.3)	0.37* (2.1)	-	0.66 (5.4)	1.44	0.01621
	-0.12 (0.3)	-	0.26 (0.7)	0.46 (3.0)	1.61	0.01541
	-	0.04 (0.2)	0.13 (0.8)	0.44 (2.9)	1.61	0.01542
5	0.08 (0.2)	-	0.27 (0.8)	0.71 (6.5)	1.63	0.01689

Notes:

a) Parameters a and b of the Fair-Shiller regression (7); t-values in parentheses; * denotes significance of the forecast in the Fair-Shiller regression at the five-percent level;
 SEE=standard error of the estimation

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