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Estimating and forecasting production and orders in manufacturing industry from business survey data: Evidence from Switzerland based on structural patterns from 1990-2000

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Arbeitspapiere/ Working Papers

Richard Etter, Michael Graff

Estimating and Forecasting Production and Orders in Manufacturing Industry from Business Survey Data.

Evidence from Switzerland based on
Structural Patterns from 1990–2000.

Estimating and Forecasting Production, Sales and Orders in Manufacturing Industry from Business Survey Data: Evidence from Switzerland based on structural patterns from 1990–2000

1 Introduction

Since general economic activity is highly sensitive to the developments in the manufacturing industry, data on industrial production, sales and orders are key inputs for analyses of business cycles. However, a major drawback is the considerable compilation and publication lag regarding official data. Moreover, to keep these lags as short as possible, the latest published data are nowadays usually provisional and subject to repeated and substantial revisions.

Therefore, a fundamental issue for policy oriented business cycle research is access to leading – or at least coincident – and reliable indicators of economic activity in manufacturing industry. To this end, the Swiss Institute for Business Cycle Research (KOF)¹ regularly conducts detailed monthly and quarterly business tendency surveys amongst Swiss manufacturing firms.

This paper analyses, how the information from the KOF surveys is related to the official production, sales and order statistics generated independently and published by the Swiss Federal Statistical Office (Bundesamt für Statistik, henceforth SFSO). While both data bases refer to the same industrial activity and the same classification of industrial activities, they are quite different in nature: KOF survey data are of a qualitative character (perceived improvement, deterioration or no change with respect to a given topic or judgements) mostly on a monthly base, whereas SFSO data are quarterly time series of quantitative indices.

Obviously, there is a trade-off between early availability and precision of indicators for economic activity. With respect to this, business surveys generate data as early as possible, whereas final official statistics are processed post hoc, thereby relying on more – and probably better – information. These two sources of information are therefore complements rather than substitutes. While business surveys are conducted to indicate actual economic conditions and trends for the near future,² official statistics are expected to give a reliable picture of the past.

Accordingly, at any point t in time, an observer of economic activity has – among other sources which are not discussed in this paper – access to the following set of information:

$$I_t = \{BTS(t)_t, BTS(t+u)_t, OSP(t-v)_t, OSF(t-w)_t\},$$

where $BTS(t)$ refers to information from business tendency surveys on present conditions, $BTS(t+u)$ to information from business tendency surveys on conditions with a lead of u , $OSP(t-v)$ to information from provisional official statistics on past conditions with lag v , and $OSF(t-w)$ to final official statistics on past conditions with lag w , and $w > v > 0$.

1 This acronym is derived from German "Konjunkturforschungsstelle".

2 For international experience with BTS see e.g. OPPENLÄNDER (1996). For Switzerland, see ETTER (1985).

If both BTS data and official statistics refer to the same empirical representations in a reasonable way, first of all, they should correlate, and a failure to do so would cast serious doubt on at least one of the data collecting and generation processes.

Consequently, a significant correlation between quantitative data from business surveys and final official statistics – with a properly specified lead-lag structure, i.e. $BTS(t) \leftrightarrow OSF(t)$ or $BTS(t+u) \leftrightarrow OSF(t+u)$ – justifies the practical use of the entire set of information I_t as specified above.

Moreover, since BTS data are available with a considerable lead before official statistics (provisional or final), it is important to have an idea on the extent to which OSF data can be derived as functions $f[BTS(t)_t]$ from coincident BTS indicators or $g[BTS(t+u)_{t-u}]$ from leading BTS indicators, respectively. On this basis, the deficiency of information from BTS data due to this forecast error can be evaluated with respect to the gain due to the availability lag of OFS data, which is equal to w for coincident indicators, and amounts to $w + u$ for leading indicators from business surveys.

For *provisional* official statistics, the availability lag is reduced by $w - v$ and thus amounts to v and $v + u$, respectively. However, since provisional statistics are by their very nature subject to – sometimes substantial – revisions, the reduction of the availability lag comes at the cost of considerable uncertainty. In this respect, an advantage of BTS data is that the original data are final. Formally, the informational content of the elements of I with respect to the true, but unknown realisation of economic conditions T_t can be represented by

$$\begin{aligned} T_t &= f[BTS(t)_t] + \varepsilon_{BTS(t)_t} \\ &= g[BTS(t+u)_{t-u}] + \varepsilon_{BTS(t+u)_{t-u}} \\ &= OSP(t-v)_{t+v} + \varepsilon_{OSP(t-v)_{t+v}} \\ &= OSF(t-w)_{t+w} + \varepsilon_{OSF(t-w)_{t+w}}, \end{aligned}$$

where $\varepsilon_{BTS(t)_t}$ and $\varepsilon_{BTS(t+u)_{t-u}}$ are the estimation and forecast errors for T_t from coincident and leading business survey indicators, $\varepsilon_{OSP(t-v)_{t+v}}$ stands for the deviation of the provisional official number from the true value of R_t , and $\varepsilon_{OSF(t-w)_{t+w}}$ denotes the final error in the official data.

Note that $\varepsilon_{OSP(t+v)_{t-v}}$ can be further decomposed into the final error plus the revision R between the provisional and the final official statistics

$$\varepsilon_{OSP(t+v)_{t-v}} = \varepsilon_{OSF(t-w)_{t+w}} + R.$$

Hence, R can be inferred at time $t + w$ from $\varepsilon_{OSP(t+v)_{t-v}} - \varepsilon_{OSF(t-w)_{t+w}}$.

Accordingly, an *ex post* analysis of the correlation structure between BTS data and official statistics needs to look at $BTS \leftrightarrow OSF$ only, since the provisional data OSP are subject to the error R , which in itself carries no meaningful information – at least if it can be taken for granted that the statistical office processes its data without bias, and their revisions are caused by new data only.

On the other hand, for an evaluation of estimations of T_t by f [BTS(t)] or g [BTS($t+u$)], as long as the final official data are not at hand, the best reference series is OSP, since the expected value of OSF(t) at time $t + v$ should follow $E[OSF(t)] = OSP(t)_{t+v}$.³

2 The Data

For Switzerland, the general picture drawn above manifests itself in the same typical manner. Specifically the informational basis regarding industrial activity comprises the following main sources:

- OSP and OSF: official statistics on production, sales and orders published quarterly by SFSO ("Der Geschäftsgang im sekundären Sektor: Die Produktions-, Auftrags-, Umsatz- und Lagerindizes").
- BTS: Business surveys are conducted by various institutions and research departments in Switzerland. Among these, the KOF surveys in the manufacturing industry, which were initiated already in the 1950s and rely on extensive information, are probably giving the most representative picture of business conditions in the Swiss manufacturing industry.

2.1 Official Statistics

Following their present definitions, SFSO data on the manufacturing industry are available from 1996:1 only. This partly is due to the fact that in the past, Switzerland has been rather reluctant to join supranational institutions in Europe (or elsewhere) and accordingly, until recently, there was less need or pressure to adapt its own statistical classifications, standards and procedures to common practice than in many other industrialised countries. Be this as it may, official statistics referring to industrial activity in Switzerland are no longer available for years before 1990, so that there is an effective restriction which we have to acknowledge.

Presently, we can thus refer to roughly five years of industrial statistics, i.e. 40 quarterly observations, which is a rather short range for the detection of cyclical patterns. Fortunately, the last six years of the pre 1996 data have been recalculated and adapted as closely as possible to the current standards, so that there are now official index series going back as far as 1990:1.

At the time of writing this (July 2002), the latest provisional data in the SFSO series published in the end of June 2002 refer to 2002:1, and the latest final official data are for 2001:1, i.e. the last four observations (2001:2–2002:1) are provisional and subject to revisions. (The next publication of official data is scheduled for the end of September.)

Accordingly, in our general notation developed above, the availability lag v for the OSP data amounts to 3–6 months or roughly 1½ quarters, and for the final OSF data one has to wait for another year, so that w equals at least five quarters.

3 We emphasise that this is conditional on the unbiasedness of the provisional data, i.e. by the professional skills and working standards within the statistical office. Since we have no a priori reason *not* to make this assumption, we leave the statistical investigation of $OSP \leftrightarrow OSF$ for an other paper and continue (1) with the observation that OSP is affected by an error R which is eliminated in the final data OSF on the basis of new information, and (2) with the assumption that R is 'white noise' with an expected mean value of zero.

2.2 *The Swiss KOF Business Survey*

The Swiss Institute for Business Cycle Research (KOF) is an institute of the Swiss Federal Institute of Technology (ETH) Zurich and a non-profit organisation. Its major activity is to analyse and forecast economic development in Switzerland. Regular surveys (business, investment and innovation surveys) provide an up-to-date, comprehensive information system for the short- and medium-term analysis of the overall economy, for individual branches of industry, and for cantonal/regional studies.

This study makes use of KOF data computed from the monthly and quarterly surveys in the Swiss manufacturing industry,⁴ which are conducted since the 1950s. The latest data referred to in this study are from the surveys for June 2002 on a monthly basis, i.e. for 2002:2 on a quarterly basis, respectively.

There are three possible answers to each qualitative question. The appraisals may be stated as too high, normal, too low, and the changes as up, unchanged and down. The weighted⁵ answers are aggregated to form percentages of each category of the total. For general purposes, the three response categories are first quantified as shares of the total, and then the balance technique is used to get a single index, i.e. the difference between the positive and the negative shares.⁶ Accordingly, the KOF data are quantified as percentages of all respondents for each category of answer and as balance indicators of the 'improvement' and 'deterioration' replies.

In this study, we draw on the whole set of indicators from the KOF surveys in manufacturing industry. Specifically, we do not look exclusively at the balance indicators, but also at the three response categories (plus equal, and minus). Since this is rarely done in other studies, we dispose of a comparably large set of potential coincident and leading indicators. (In what follows, the series derived from KOF data will carry the suffix P, G, M and B for identification.)

Before correlating these series with series from OSF statistics, some transformations are necessary. Firstly, the monthly survey data X are aggregated into quarterly series (mean values A and, alternatively, end values E), where

$$A(X)_Q = (X_{m1} + X_{m2} + X_{m3}) / 3$$

and

$$E(X)_Q = X_{m3} .$$

Secondly, the KOF series are used alternatively in original (X_0) and deseasonalised form (X_1).

Thirdly, apart from the level series, we compute first differences with respect to the preceding quarter ($t-1$) as well as with respect to last year's corresponding quarter ($t-4$):

4 For questionnaires see <http://www.kof.ethz.ch/>.

5 The weights on the micro-level is the firm's employment; weights on aggregate level are demographic data.

6 This method of extracting relevant information is widely used. For a discussion of its properties, see DASGUPTA/LAHIRI (1992).

$$D1(X) = X_t - X_{t-1},$$

$$D4(X) = X_t - X_{t-4}.$$

These quantifications and transformations obviously lead to a very large number of series: For each item X in the monthly survey questionnaires, there are 4 quantifications (P, G, M, B), 2 aggregations into quarterly series (A, E) as well as original and deseasonalised alternatives (0, 1). This number of series is multiplied further by factor 3, since all of these are evaluated alternatively in levels, differences (D1) and seasonal differences (D4). Accordingly, one single item in the questionnaire can result in a maximum of 48 ($4 \times 2 \times 2 \times 3$) quantitative series.

Since the comparable KOF series are going back well beyond 1990, our statistical analysis can draw on the full informational basis of the official data from the 1990s to the present, with some reservations regarding a structural break or shift in the SFSO series after 1995:4 due to the introduction of the present standards in 1996:1.

Since general experience suggests that BTS data allow reasonably reliable forecasts of economic conditions at least one quarter ahead, the total lead of forecasts from estimations by $g[\text{BTS}(t+u)]$ before the availability of final official data $\text{OSF}(t-w)$, i.e. $u + w$, can be expected to be at least $1\frac{1}{2}$ years.

The lead reduces to roughly $1\frac{1}{4}$ years, when coincident BTS indicators are referred to, so that $T_t = f[\text{BTS}(t)]$, which is, however, still a considerable lead for practical purposes.

In what follows, this paper will focus on parsimonious specifications of $f[\text{BTS}(t)]$ and $g[\text{BTS}(t+u)]$. To this end, we shall present several selection criteria for bivariate and multivariate regressions of OSP on BTS data with pre-determined leads. In order to keep the procedure as transparent as possible, we restrict the number of regressors to a maximum of two. Moreover, since this study is exclusively concerned with estimates of type $\text{BTS} \rightarrow \text{OSF}$, we refrain from use of autoregressive forecasts within a given OSF series as well as cross-reference within different OSF or OSP series.⁷ Thus, this study does not aim at finding specifications of forecast models which reveal the *best fit* with respect to a given OSF series – these would probably include autoregressive elements as well as cross references with the data corpus of OSF –, but to identify a set of KOF BTS indicators which are coincident or leading indicators for industrial activity in Switzerland.

⁷ If the data generation process within the statistical office is (totally or in part) a black box for outsiders, the last point is essential: As far as autoregressive techniques and cross reference are practised, outsiders can improve the precision of their estimates with respect to a reference series by same means, but the results would be partly tautological.

*Table 1: Questions of the KOF BTS in manufacturing industry**Monthly survey*

1a	Order income compared to previous month
1b	Order income compared to the month of the previous year
2a	Order books compared to previous month
2b	Order books, judgement
3a	Production compared to previous month
3b	Production compared to the month of the previous year
4a	Stocks of intermediate products compared to previous month
4b	Stocks of intermediate products, judgement
5a	Stocks of finished products compared to previous month
5b	Stocks of finished products, judgement
6a	Expected incoming orders (next three months)
6b	Planned production (next three months)
6c	Planned purchase of intermediate products (next three months)
7	Expected midterm development (beyond the next three months)

GG*	Business activities
PL*	Plans of firms

Quarterly survey

1a	Employment compared to previous quarter
1b	Employment, judgement
2a	Technical capacities compared to previous quarter
2b	Technical capacities, judgement
2c	Degree of capacity utilisation, percentage
4	Profit situation compared to previous quarter
8b	Expected prices for intermediate products

* aggregated index.

3 *Previous Studies*

There is a number of studies from various countries, which screen the correlation of BTS data with official statistics, and some of these studies undertake to refer to BTS data in order to estimate the official data. Unsurprisingly, the results are mixed, but generally, BTS data seem to be extremely useful for the construction of coincident and leading indicators of economic activity. However, for Switzerland, the earlier evidence is comparably unfavourable, so that a new look at the data is in order.

An earlier attempt to derive numerical estimates of the Swiss official statistical production index by means of KOF BTS data failed to find sufficiently close correlations and attributed this – at least in part – to the dubious quality of the reference series, the BIGA produc-

tion index⁸ from 1980:1–1989:3 (STALDER 1998, pp. 35–36). Since official data, which are adapted to the new SFSO production index, have not been calculated for the years before 1990, there is no direct way to address STALDER'S assumption. If, however, the post 1990 official statistics series are plagued less by data problems than the previous, pre 1990 official series, the correlation between OSF data and quantifications of BTS data could meanwhile have improved, thereby providing a better basis for $BTS \rightarrow OSF$ estimates.

Similar work has been done by TAKALA/TSUPARI (1997) for Finland. They analysed the behaviour of the balance indicators in total manufacturing industry and in some important branches compared with yearly growth rates of industrial production. After a cross-correlation analysis, Granger causality tests were conducted to select the leading indicators. As an additional feature they ended with some cross-spectral analysis to find the optimal time lead.

FRITSCH (1999) analysed the well known ifo data for Germany. The empirical work started with a graphical interpretation of the leading properties of expectation indicators at economic turning points. Cross-correlation and Granger causality tests confirmed the leading characteristics of the used data. Unfortunately a detrended reference series was used giving the change-questions a lead by definition, therefore the effective lead would be somewhat smaller than the published one.

Another approach was chosen by HÜFNER/SCHRÖDER (2001). They analysed a set of coincident survey indicators with respect to leading survey indicators. To this end, they started with a graphical analysis and continued with cross-correlation and Granger causality tests. There were no significant differences in the prognostic power, particularly in signalling changes in the direction of industrial production. However, the results are somewhat difficult to interpret because HÜFNER/SCHRÖDER did not use a reference series.

In the USA, MOORE ET AL. (1994) analysed the behaviour of the cumulated balance indicators of different surveys in the CIBCR Leading Index, which is a highly reliable indicator for detrended economic development. The qualitative survey indicators showed a smoother performance, but the lead was not quite as long as with the quantitative indicators.

For Switzerland, MARTY (1997) analysed – among other indicators – the KOF BTS indicators. He proceeded in a way similar to our study; but his reference series was GDP and not industrial production, because at that time the revised index of industrial production covered only six years. After the selection process by cross-correlation and graphical interpretation of turning points, the remaining indicators entered the principal component method to aggregate them to the new leading indicator "KOF barometer", which in Switzerland is nowadays widely referred to with respect to potential short and medium term turning points in GDP growth. However, this indicator focuses exclusively on turning points and thus does not make any reference to levels.

4 *Empirical Analysis*

The informational basis of the KOF BTS data is quantified as described above, and the OSF data (Y) are referred to as original index series, quarterly (QTQ) and year to year (YTY) growth rates without further transformations, where

8 Recall that official industrial statistics in Switzerland underwent major changes in the 1990s. In this context, "BIGA indices" denote the former series.

$$QTQ \equiv WR1(Y) = \ln Y_t - \ln Y_{t-1}$$

and

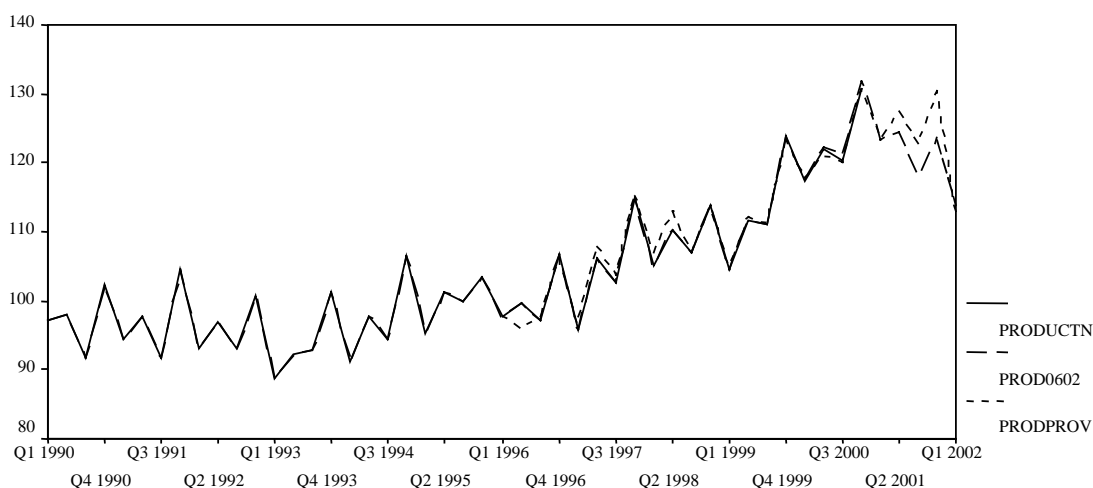
$$YTY \equiv GR4(Y) = \ln Y_t - \ln Y_{t-4}.$$

Among the SFSO index series, production and sales are highly correlated, so that in this paper, we do not report results for the sales series.⁹ Moreover, since the production series is conceptually non-stationary and, in addition to this, strongly affected by seasonal factors,¹⁰ we refer to the production index YTY growth series only.

The basic analyses refer to OSF data from 1990:1 to 2000:4, i.e. to 44 observations for the level series, 43 for quarterly growth rates and 40 for year to year growth rates.

The following time series plots (charts 1 and 2) show the official Swiss production index. The solid line (PRODUCTN) denotes our within sample reference series. It ranges from 1990:1 to 2000:4 and is final with the exception of the last four quarters, which is how the data presented itself in spring 2001. For out of sample analyses, we can thus refer to new data released after that time, which at the time of writing are up to 2002:1, where the last 4 quarters are provisional (PROD0602). To get an idea of the extent to which this series has been subject to revisions R in the past (since the introduction of the new statistical standards in 1996), we plot a third series (PRODPROV), which shows the provisional values of the production index at the time of their first publication.

Chart 1

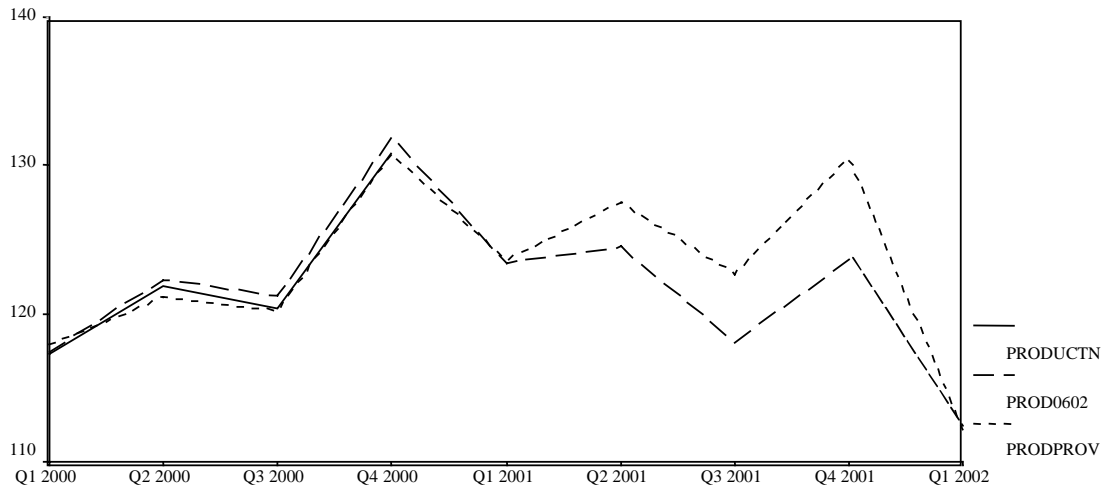


9 Since the production series are mainly derived from the sales series, it might seem preferable to report the results for the sales index, and as a matter of fact, the correlation between the sales index and our BTS data is slightly higher than for the production index. However, the results do not differ in any substantial manner, so that for the sake of better comparability with other studies, we report production rather than the sales.

10 Similar observations have been made for other economies, e.g. for Sweden (BERGSTRÖM 1995). The seasonal pattern in the Swiss OSF data (poor performance in the first and third quarters, good performance in the second and fourth quarters) have been cross-checked with other information, and no hints have been found for computational problems. An explanation could refer to the Swiss holiday pattern, but here we have to leave this question open for further investigation.

Since the latest observations are of special concern for the out of sample estimations and forecasts (see below), the second graph (chart 2) shows a stretched picture of the last few observations (2000:1–2002:1) for PRODUCTN, PROD0602 and PRODPROV, where, PROD0602 is the out of sample part of the production index series which we shall later try to estimate by means of KOF data and the structural relations inferred from PRODUCTN.

Chart 2



This series as well as the other 4 main industrial statistics series published by the Swiss Federal Statistical Office (sales, incoming orders, order books and inventories) are given for various levels of aggregation according to the NOGA classification (corresponding down to the 4-digit-level to the NACE, Rev. 1, of the EU), and in many cases, we were able to find a matching subaggregate in the KOF BTS data. An extensive screening of the data by means of some 10,000 cross correlations revealed, however, that – for whatever transformation of either series – the narrower the aggregate, the lower is the correlation between OSF and KOF BTS data (ETTER/GRAFF 2001). From this very strong regularity, we are inclined to infer, that a considerable amount of the noise in the 2- and 3-digit categories is cancelled out in the aggregate data.

Therefore, in this paper, we restrict the presentation to the aggregate level NOGA D (manufacturing industry), which is a subset of the total 'secondary sector'.¹¹ As we are interested to identify coincident or leading BTS indicators, in order not to sacrifice any information from the OSF series, the BTS series have to refer to additional, earlier observations. The main lead considered here is seven quarters, and none of the KOF series pose any difficulty in this respect, so that our number of paired (or multivariate) observations ranges from 40 to 44 throughout this paper.

The second OFS series that we shall analyse in this paper is the incoming orders index (ORDER). The reason for this choice is that in business cycle analysis, incoming orders are frequently referred to as leading indicators for overall industrial activity, hence, any hints referring to this series might prove a valuable tool for policy oriented analysis.

¹¹ From the larger total 'secondary sector', NOGA D excludes extracting industries, construction as well as energy and water supply, which are known to follow different patterns of business activity than manufacturing.

4.1 *Cross-Correlations*

With the series and time range as described above, a large number of cross-correlations were computed to screen the data for pairs of highly correlated KOF and SFSO series on the aggregate industry level as well as 12 two-digit industries. From these, all pairs where the maximum correlation showed up simultaneously or with a lead (the maximum potential lead considered being seven quarters) of the KOF series were selected for further analyses (Granger causality, pattern of turning points). This resulted in the identification of all 'highly' correlated pairs of series with predetermined and stable lead-lag structures, where the selection threshold was predetermined as

$$|r| \geq 0.7 \Leftrightarrow r^2 \geq 0.5.$$

The results referring to the YTY growth rates of the production and the incoming order index, GR4PRODU and GR4ORDER, are presented in table 2, which shows the (maximum of) 10 pairs with highest absolute correlations for any predetermined lead λ ($7 \geq \lambda \geq 0$).

4.2 *Turning Point Analysis*

In the economic literature, going back to BURNS/MITCHELL (1946) there are different theoretical concepts of business cycles, and accordingly turning points are differently dated (AMSTAD 2000). A common concept is oriented at the growth rate of one or more economic indicators and comes under the heading of acceleration/deceleration. This concept looks at points of extreme growth rates, i.e. mathematical points of inflection, and is based on the dynamics of the economy. At the same time, it distinguishes between positive and negative growth rates; and this distinction is used to define the phases of the classical cycle, where a recession is commonly defined by at least two consecutive time periods with negative growth rates.

Other concepts are oriented at the degree of capital utilisation and distinguish between phases of normal use of capital, bottlenecks or overcapacities. This corresponds to the growth cycle concept, which goes back to the work of MINTZ (1969). There, growth cycles are defined as different states between points of extreme deviation from an average trend. By definition, downturns will come earlier, upturns later in trend-adjusted series with upward trends than in unadjusted series. Therefore upswings will be shorter and downswings longer than in classical cycles.

With respect to forecasts of economic trends, the interest of policy makers is concentrated on hints to the dynamics of GDP growth, or of industrial production, and these are commonly assessed by (yearly) growth rates. Our definition of turning points is therefore based on the concept of acceleration/deceleration. Specifically, a turning point is dated the last quarter of a tendency's direction, if the quarter with the change of tendency is followed by two quarters where the tendency is at least not opposed to the new tendency. At the beginning and the end of a time series we apply the rule of BRY/BOSCHAN (1971), which says that a turning point cannot be defined in the first or the latest two quarters of a time series.

Referring to this concept, for our official statistics, the analysis of turning points has to be limited to the GR4(Y) series (year to year growth rates of quarterly data), which are conceptually stationary. The BTS data under consideration – balance, plus-, equal-, minus-percentage – are by definition stationary. We compare the OSF and the BTS data under the following conditions:

Table 2: Cross-Correlations, NOGA D, leads BTS before OSF ≥ 0

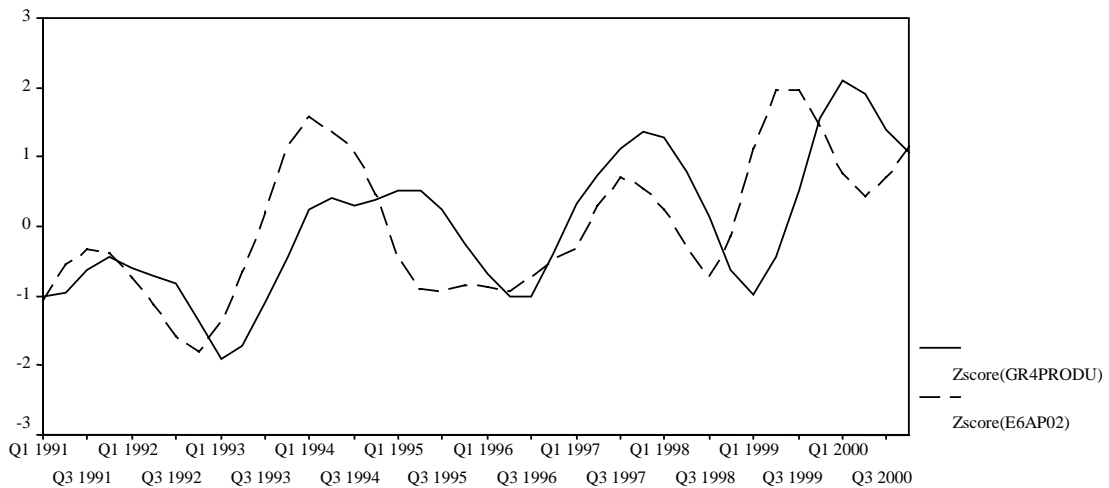
OSF series	KOF BTS series	r max.	Lead BTS→OSF (in quarters)
GR4PRODU	E6AP1	.723	2
GR4PRODU	E6BS1	.814	1
GR4PRODU	E6CS1	.812	1
GR4PRODU	E6AM1	−.803	1
GR4PRODU	EPLS1	.800	1
GR4PRODU	E7_M1	−.795	1
GR4PRODU	E6CP1	.790	1
GR4PRODU	E2AM1	−.785	1
GR4PRODU	E6CS0	.785	1
GR4PRODU	E6BS0	.784	1
GR4PRODU	E6AS1	.783	1
GR4PRODU	A1BM0	−.878	0
GR4PRODU	EGGS0	.874	0
GR4PRODU	A1BS0	.869	0
GR4PRODU	Q4_S1	.863	0
GR4PRODU	E1BM0	−.861	0
GR4PRODU	AGGS0	.860	0
GR4PRODU	Q4_M1	−.860	0
GR4PRODU	E1BS0	.848	0
GR4PRODU	E3BM0	−.848	0
GR4PRODU	A1BP0	.842	0
GR4ORDER	E6AS1	.799	1
GR4ORDER	D4A6BP0	.785	1
GR4ORDER	D4A6BP1	.784	1
GR4ORDER	D4E6BS0	.772	1
GR4ORDER	D4E6BP0	.770	1
GR4ORDER	D1AGGS0	.769	1
GR4ORDER	D4E6BS1	.768	1
GR4ORDER	D4E6BP1	.764	1
GR4ORDER	D4A6CP0	.764	1
GR4ORDER	D4A6CP1	.764	1
GR4ORDER	E1BS0	.891	0
GR4ORDER	E1BM0	−.888	0
GR4ORDER	A1AM1	−.887	0
GR4ORDER	A1AS1	.877	0
GR4ORDER	Q4_S1	.875	0
GR4ORDER	E1BP0	.874	0
GR4ORDER	A2AS1	.871	0
GR4ORDER	Q4_M1	−.870	0
GR4ORDER	A2AM1	−.869	0
GR4ORDER	Q4_S0	.849	0

- The two time series fulfil the correlation criteria of chapter 4.1, and
- if the cross-correlogramme indicates a lead of BTS, then a Granger causality test (see GRANGER 1969) is significantly rejecting the null hypothesis for $BTS_{t-k} \rightarrow OSF_t$ with $p \leq 1\%$.¹²

All analysed time series were smoothed over the respective analysed period (OSF: 1990:1–2000:4; BTS: 1985:1–2000:4) by the CENSUS-X11 procedure, because original data of economic time series of the type used here include a high part of seasonal and stochastic elements. Therefore, a sensible fixation of turning points has to be based on the smooth component. Chart 3 illustrates the graphical matching of the standardised and smoothed series for GR4PRODU and the indicating variable E6AP (deseasononaised quarterly end value of 'increasing' response to item 'expected incoming orders'), where the cross-correlation (table 2, first line) indicates a lead of two quarters for BTS series.

Chart 3

Turning points in manufacturing industry: Z-values of the reference series GR4PRODU and of E6AP with a lead of two periods



To avoid effects of marginal changes of the smoothed time series on the fixation of turning points, we rounded the standardised time series and to one decimal point. Hence, the analysis of the changes of a series was performed in discrete steps of 0.1 standard deviations. Finally, attention has to be given to the fact that, by definition, after an upper (lower) turning point, there can follow – if any – only a lower (upper) turning point.

12 After a first identification of the predominant lead-lag structure between a given pair $BTS \rightarrow OSF$, a confirmatory Granger causality test was conducted by regressing the OSF series on its lagged value as well as the lagged value of the preselected BTS series,

$$Y_t = \beta_0 + \beta_1 Y_{t-\lambda} + \beta_2 X_{t-\lambda} + \varepsilon_t,$$

where the lag λ for both regressors was fixed equal to the lead of the BTS series before the OSF series as identified by the maximum correlation in the cross-correlogrammes. Only very few of the preselected pairs failed to pass the test $\beta_2 \neq 0$. For details, see (ETTER/GRAFF 2001).

Then, the upper and the lower turning points of the OSF time series were identified. These serve as the reference points for the BTS time series. After this, the development of BTS series to the correspondent OSF series was analysed with respect to the lead-lag structure. In this context, note that apart from indicating a given turning point in the reference series, a control series can fail to signalise a turning point, or it can indicate a turning point, where there is none in the corresponding OSF series, and this has to be accounted for.

Summarising quality criteria

Since a comparison of the OSF and the BTS series with respect to their turning points has to account for different aspects, we calculated two different summary measures. This will later enables us to select the "best" BTS time series as regressors in our approach first to reproduce the definitive values of the historical OSF time series, and then to refer to the regression parameters to compute estimates of the provisional and forecasts of the future values of these OSF series.

- The first measure is the average lead (AVL) at all (upper and lower) turning points of a BTS time series with respect to the corresponding OSF data. Generally, leading indicators are strong at the average lead, but often fail to lead at the turning points, thereby failing to provide what is perhaps the most relevant information for users.
- The second measure is our index of quality (QI) at turning points. We define this index is as follows:

$$QI = \frac{NCS - NFS}{NTP} ,$$

where NCS is the number of correct signals by the BTS indicator, NFS is the number of false signals and NTP is the number of the turning points in the reference series. Note that QI assumes its maximum value 1.0 for an indicator series which signals all turning points of the reference series correctly and, in addition, does not give any false signals. On the other hand, any false or missing signal is reducing the index by the same increment.

4.3 OLS Regressions

We can now proceed with four criteria to judge the coherence between an OSF reference series and a BTS time series:

- cross-correlation coefficient,
- Granger causality test,
- deviation of average lead at turning points (AVL) from lead λ at maximum $|r|$,
- quality at turning points index (QI).

The results for the KOF BTS series with the best predictive and coincident properties with respect to our OSF reference series, YTY growth of production GR4PRODU and YTY growth of incoming orders GR4ORDER, are shown in table 3. To construct this table, we picked for each reference series and each lead for the BTS series $\lambda \geq 0$ the transformation of the BTS series which yields the highest absolute correlation.

Table 3: Best pairs with respect to selection criteria, NOGA D, leads BTS before OSF ≥ 0

OSF	BTS	Lead BTS	r max.	AVL	QI
GR4PRODU	E6AP1	2	.723	2.1	1.0
GR4PRODU	E6BS1	1	.814	0.7	1.0
GR4PRODU	E6CS1	1	.812	1.0	1.0
GR4PRODU	E6AM1	1	−.803	1.9	1.0
GR4PRODU	EPLS1	1	.800	0.8	0.9
GR4PRODU	E7_M1	1	−.795	0.4	1.0
GR4PRODU	E2AM1	1	−.785	0.3	1.0
GR4PRODU	A1BM0	0	− .878	−0.4	1.0
GR4PRODU	EGGS0	0	.874	− 0.3	0.9
GR4PRODU	Q4_S1	0	.863	0.4	1.0
GR4PRODU	E3BM0	0	−.848	−0.9	0.9
GR4ORDER	E6AS1	1	.799	0.9	1.0
GR4ORDER	D4A6BP0	1	.785	0.4	1.0
GR4ORDER	D1AGGS0	1	.769	0.9	1.0
GR4ORDER	D4A6CP0	1	.764	0.4	1.0
GR4ORDER	E1BS0	0	.891	0.6	1.0
GR4ORDER	A1AM1	0	−.887	−0.9	1.0
GR4ORDER	Q4_S1	0	.875	− 0.3	1.0
GR4ORDER	A2AS1	0	.871	−0.4	1.0

The selection of a single best leading or coincident indicator for an OSF time series, however, is complicated by the fact that these criteria do not have a hierarchical structure. Hence, the choice of an indicator has to refer to the needs or preferences of the potential user. This selection problem is illustrated by the bold entries in table 1, which indicate the best result with respect to one of the criteria, given a specific lag-period. For example, with respect to the reference series GR4PRODU, with a lead of two periods, E6AP1 scores best in all criteria, and the same is true for GR4ORDER and E6AS1 with a lag of one period. But for prognostic means of GR4PRODU one period ahead, there are two alternatives. If the best average fit is given priority, one would choose E6BS1; however, if the interest is directed towards best performance at turning points, one would choose E6CS1. Likewise, alternative regressors show up for GR4PRODU at $\lambda = 0$ (A1BM0 vs. EGGS0) as well as for GR4ORDER at $\lambda = 0$ (E1BS0 vs. Q4_S1).

Referring to these pairs, as shown below, rather precise ex post-estimates of SFSO data are obtained through regressions of the production and incoming orders index series on just one coincident or – though to a lesser extent – leading series from the KOF business surveys:

$$Y_t = \beta_0 + \beta_1 X_{t-j} + \varepsilon_t.$$

To improve the fit further, we consider a structural break regarding the stability of the parameters between 1995/1996 due to the introduction of the new official statistics, so that

$$Y_t = \beta_0 + \beta_1 D + \beta_2 X_{t-j} + \beta_3 D \times X_{t-j} + \varepsilon_t,$$

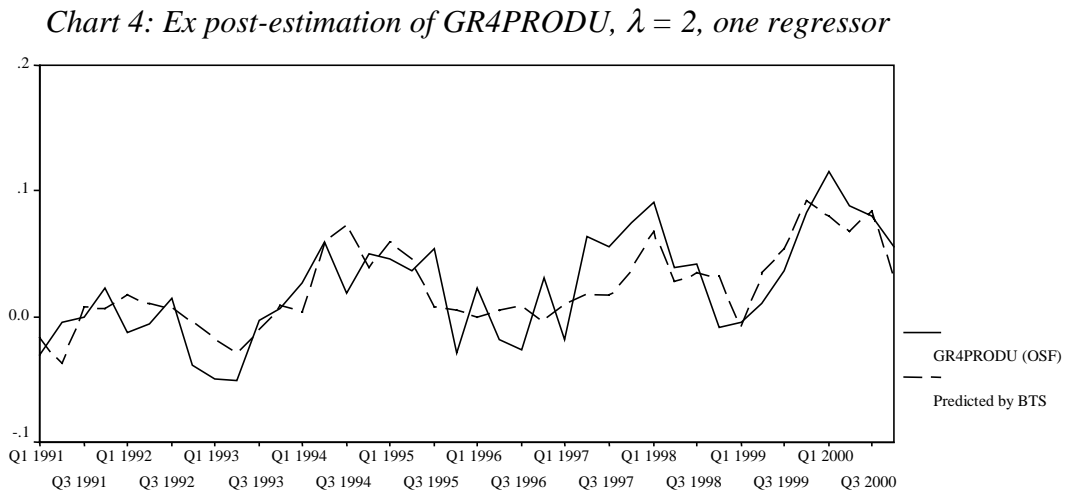
where $D = 0$ for quarters until 1995:4, and $D = 1$ thereafter. If the F-test for joint significance of D and $D \times X_{t-j}$ turns out to show a $p \leq 0.1$, the second regression is fitted, if $p > 0.1$, we fit the simple model (see BROWN ET AL. 1975).

A summary of the bivariate regression statistics is given in table 4. To give a feeling for the within sample estimates, the first estimation result is visualised in chart 4, which shows a plot of the GR4PRODU series and the within sample estimate by means of E6AP1 with a lead of two quarters. Though the fit for this regression with an R^2 of 0.59 is not particularly high, the plot shows that the predicted series tracks the OSF series reasonably well.

Table 4: Regressions: OSF on one BTS series

OSF	BTS	Lead BTS	F	R ²
GR4PRODU	E6AP1	2	1.60	0.59
GR4PRODU	E6BS1	1	0.89	0.74
GR4PRODU	E6CS1	1	2.30	0.73
GR4PRODU	A1BM0	0	2.55*	0.80
GR4PRODU	EGGS0	0	1.10	0.76
GR4ORDER	E6AS1	1	1.19	0.72
GR4ORDER	E1BS0	0	3.13*	0.82
GR4ORDER	Q4_S1	0	0.33	0.76

* $p \leq 0.10$; regression with two additional regressors for structural break.



There is, however, room for an obvious improvement of these estimates, since as additional regressors can be included into the model. This final step of analysis is presented in the following section.

4.4 Multivariate Regressions: Regressor Selection Procedures and Out of Sample Estimations/Forecasts 2001:1–2002:3

Any OLS regression fit can be improved by additional regressors, however, it is well known that multicollinearity can severely impair the precision of the coefficient estimates, thereby rendering such a regression less useful for analytical purposes.

In the context of this paper, this implies that the overall fit of our within sample regressions can successively be improved by the inclusion of other BTS series as regressors, but, due to multicollinearity, the estimated parameters are then at the same time successively getting less close to what might be meaningful structural relationships. Accordingly, the within sample fit cannot be increased without the potential 'cost' of affecting the usefulness of the regression results for out of sample forecasts.

To cope with this problem, one strategy is to reduce the set of potential regressors to a number of orthogonal – uncorrelated – variables by means of principal component analysis. Another option is to address the problem of multicollinearity directly by an analysis of the intercorrelations between the potential regressors.

Since this is an explorative study, we want to keep the procedure as transparent as possible. Therefore, we derive specifications of $f[BTS(t)]$ and $g[BTS(t+u)]$ with independent explanatory variables, where the number of regressors is fixed to two. Specifically, our selection of pairs of regressors for a given OSF series considers two alternatives, where, for any predetermined lead λ , the first selection emphasises the overall fit, and the second the past performance of turning point precision.

Accordingly, the 'best overall fit' ('regressor set 1') procedure selects as a first regressor for the leading indicators approach $g[BTS(t+u)]$ and, respectively, for the coincident indicators approach $f[BTS(t)]$

- the BTS series with the highest absolute correlation to the OSF series where $\lambda \geq 1$ or
- the BTS series with the highest absolute correlation to the OSF series where $\lambda = 0$.

On the other hand, the 'turning point precision' approach ('regressor set 2') picks as the first regressors for $\lambda \geq 1$ and, respectively, $\lambda = 0$, those BTS series that performed best with respect to our turning point precision measures $AVL - \lambda$ and QI (see table 3).¹³

In either case, the second regressor for is identified by screening all BTS series that pass the initial test for $|r| \geq 0.7$ (see table 2) at $\lambda \geq 1$ or $\lambda = 0$, respectively, where the choice is made according to the lowest intercorrelation with the first regressor (see table 5).

¹³ Note that $AVL - \lambda$ and QI can give different signals. In this case, we followed a hierarchical procedure, where $AVL - \lambda$ was given priority (here: choice of EGGS0 \leftrightarrow GR4PRODU at $\lambda = 0$). Moreover, $|r|$, $AVL - \lambda$ and QI can all point to the same BTS series. In this case, we imposed the restriction regression set 1 \neq regression set 2 (here: choice of D1AGGS0 \leftrightarrow GR4ORDER at $\lambda \geq 0$).

As in the bivariate regressions, the possibility of structural breaks between 1995 and 1996 is accounted for in the multivariate regressions:

$$Y_t = \beta_0 + \beta_1 D + \beta_2 X1_{t-j} + \beta_3 D \times X1_{t-j} + \beta_4 X2_{t-j} + \beta_5 D \times X2_{t-j} + \varepsilon_t,$$

where D and $D \times X_{t-j}$ are included as regressors, if they turn out jointly significant ($df = 2$) in single regressor estimations.

In order to enable us to come up with some out of sample estimates, the endogenous OSF series are the same as in the structural analyses above, i.e. the YTY growth rate data range from 1991:1 to 2000:4, and no later revisions are considered.

The KOF BTS series, however, have been updated and now extend to 2002:2. Accordingly, with $\lambda = 0$, our coincident estimates include 2002:2 as the last quarter, and for $\lambda \geq 1$, we shall present forecasts of OSF series until 2002:3.

Recall that for a first, albeit informal, inspection of the out of sample properties of our multivariate regressions, at the time of writing, we have access to provisional SFSO data until 2002:1 and to final SFSO data until 2001:0. Accordingly, the comparison of the first out of sample observation with its $g[BTS(t+u)]$ and $f[BTS(t)_t]$ estimates refers to final SFSO data (OSF) and therefore allows a definite evaluation, whereas for the comparisons regarding the next 4 quarters, one has to bear in mind that the SFSO data are provisional (OSP). Finally, we have forecasts for up to two additional quarters, which cannot yet be compared with any official statistics.

The regression results for $g[BTS(t+u)]$ and $f[BTS(t)_t]$ are summarised in table 6. The overall fit R^2 is high for all specifications and ranges from 0.74 to 0.86. Moreover, the selection procedure for the second regressor was largely successful; most regressors yield reasonably precise estimates.¹⁴

Since, due to the fundamental data restrictions in the Swiss official statistics, we dispose of relatively few observations. Hence, we calculated a maximum of 7 out of sample estimates, and out of these, only 5 can be compared with their (still mostly provisional) reference series. Therefore, we shall not conduct any formal tests of the out of sample properties.

Instead, charts 5–8 give a graphical representation and allow an informal assessment, where the solid lines are the reference series (plotted from 1996, i.e. after the last major revision of the Swiss industry statistics), the two dotted lines are graphs of $g[BTS(t+u)]$ and $f[BTS(t)_t]$, i.e. the estimations of the reference series with leading or coincident indicators, and the vertical lines at 2001:1 indicate the beginning of the out of sample period.

¹⁴ Note that for the estimation of GR4ORDER at $\lambda \geq 1$, our selection procedure results in the same set of regressors, since the 'best fit' and the 'best turning point properties' regressors A6AS1 and D1AGGS0 are mutually less correlated ($r = 0.577$) than either of them with all other potential 2nd regressors.

Table 5: Intercorrelations between potential regressors

2 nd regressor	1 st regressor selected w.r.t. r max. turning point		lead/lag	OSF series
	E6BS1	E6CS1		
E6AP1*	.608	.593		
E2AM1	-.883	-.901		
E7_M1	-.898	-.899	leading	
E6AM1	-.903	-.907	BTS	GR4PRODU
EPLS1	.980	.988	series	
E6CS1	.968			
E6BS1		.968		
	A1BM0	EGGS0		
Q4_M1	.901	-.925		
Q4_S1	-.927	.913		
E1BS0	-.927	.932	coincident	
E3BM0	.937	-.965	BTS and OSF	GR4PRODU
E1BM0	.940	-.943	series	
A1BP0	-.954	.940		
AGGS0	-.954	.977		
A1BS0	-.989	.960		
EGGS0	.961			
A1BM0		.961		
	E6AS1	D1AGGS0		
E6AS1		.577		
D1AGGS0	.577			
D4A6CP0	.668	.850	leading	
D4A6CP1	.699	.825	BTS	GR4ORDER
D4A6BP1	.783	.761	series	
D4A6BP0	.783	.763		
D4E6BP1	.784	.734		
D4E6BP0	.785	.735		
D4E6BS1	.792	.786		
D4E6BS0	.793	.788		
	E1BS0	Q4_S1		
Q4_M1	-.873	-.946		
E1BP0	.987	.874		
A2AM1	-.876	-.924	coincident	
Q4_S0	.890	.983	BTS and OSF	GR4ORDER
A2AS1	.897	.928	series	
A1AM1	-.905	-.904		
A1AS1	.918	.905		
E1BM0	-.988	-.893		
Q4_S1	.882			
E1BS0		.882		

* series lagged 1 quarter with respect to other potential 2nd regressors.

Table 6: Regressions: OSF on two BTS series

OSF series	intercept	BTS series 1	BTS series 2	selection method	structural break*	R ²
GR4PRODU		E6BS1 $\lambda = 1$	E6AP1 $\lambda = 2$	correlation regressand with 1 st regressor	none	0.74
	-0.023 (-0.82)	0.0025 (4.46)*	0.0015 (1.33)			
GR4PRODU		E6CS1 $\lambda = 1$	E6AP1 $\lambda = 1$	turning point precision of 1 st regressor	none	0.74
	-0.0098 (-0.32)	0.0024 (4.23)*	0.0016 (1.20)			
GR4PRODU		A1BM0 $\lambda = 0$	Q4_M1 $\lambda = 0$	correlation regressand with 1 st regressor	1 st regressor	0.80
	0.13 (6.27)*	-0.0025 (-2.93)*	-0.00088 (-0.71)			
GR4PRODU		EGGS0 $\lambda = 0$	Q4_S1 $\lambda = 0$	turning point precision of 1 st regressor	none	0.78
	0.059 (13.1)*	0.0016 (2.69)*	0.0014 (1.86)*			
GR4ORDER♣		E6AS1 $\lambda = 1$	D1AGGS0 $\lambda = 1$	correlation regressand with 1 st regressor	2 nd regressor	0.86
	-0.061 (-2.92)*	0.0029 (5.07)*	0.0024 (2.22)*			
GR4ORDER♣		D1AGGS0 $\lambda = 1$	E6AS1 $\lambda = 1$	turning point precision of 1 st regressor	1 st regressor	0.86
	-0.061 (-2.92)*	0.0024 (2.22)*	0.0029 (5.07)*			
GR4ORDER		E1BS0 $\lambda = 0$	Q4_M1 $\lambda = 0$	correlation regressand with 1 st regressor	1 st regressor	0.83
	0.058 (1.48)	0.0018 (3.38)*	-0.020 (-1.39)			
GR4ORDER		Q4_S1 $\lambda = 0$	E1BP0 $\lambda = 0$	turning point precision of 1 st regressor	2 nd regressor	0.83
	-0.092 (-1.84)*	0.0015 (1.54)	0.0032 (2.89)*			

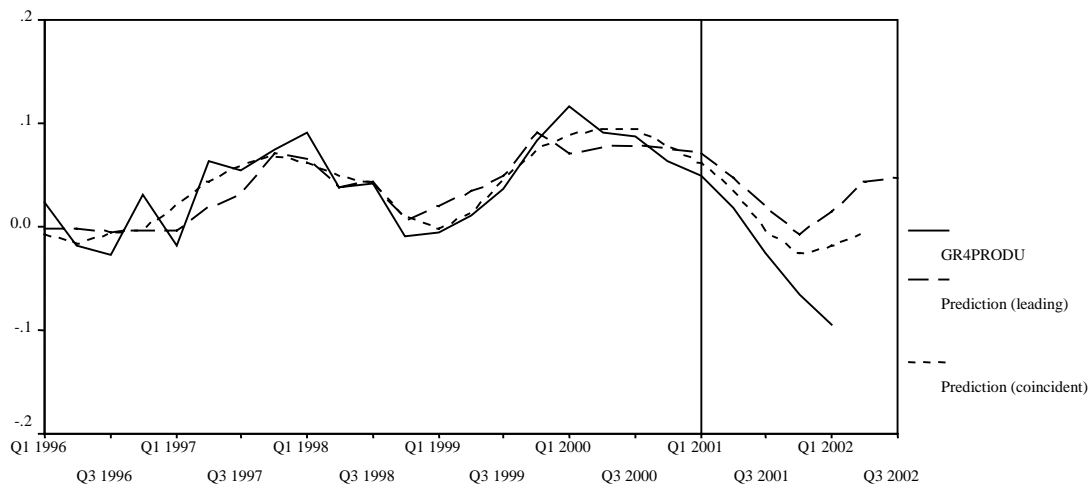
* $p \leq 0.10$; regression with two/three additional regressors D and $D \times$ BTS series (one or both) case of one or two structural breaks in bivariate regressions of OSF on either BTS series.

♣ Two identical regressions due to complementary outcome of regressor selection,

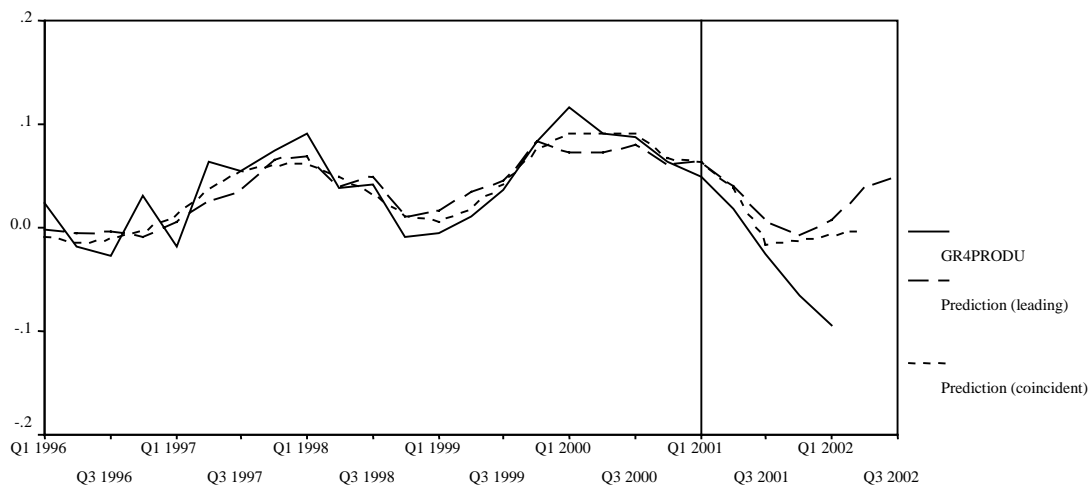
An inspection of charts 5 and 6, referring to the YTY growth rate of the production index, shows a close correspondence between WR4PRODU and its two multivariate estimations $g[BTS(t+u)]$ and $f[BTS(t)]$.

However, in the out of sample segment, there is a coherent deviation from the provisional official data, which indicate a straight downward trend without any sign of improvement of business conditions in Switzerland, whereas all estimations with KOF BTS indicators indicate a turning point.

*Chart 5: Prediction of GR4PRODU (regressor set 1:
1st regressor with $|r| \max.$)*



*Chart 6: Prediction of GR4PRODU (regressor set 2:
1st regressor with best turning point properties)*



Since in both alternative regressions – referring to the $|r| \max.$ -regressor set 1 (chart 5) or the 'best turning point properties'-regressor set 2 (chart 6) – the $g[BTS(t+u)]$ estimations, which rely on leading indicators, are resulting in considerably higher out of sample (pre-

dicted) estimates of the *levels* of growth after 2000:4 than the $f[BTS(t)_t]$ estimates, which rely on coincident indicators result in a higher *level* of growth than the coincident $f[BTS(t)_t]$ estimates, there is some evidence that the survey respondents have revised their latest assessments downward from initially too optimistic levels. In other word, presently, the coincident BTS indicators, which are derived from the most recent KOF surveys in the 2nd quarter of 2002, reflect a somewhat more pessimistic attitude among Swiss firms than the leading indicators in the preceding surveys (1st quarter of 2002 and the 4th quarter of 2001).

Nevertheless, the upward trends in the out of sample estimates of both $g[BTS(t+u)]$ and $f[BTS(t)_t]$ remain and continue into the forecast period, so only time will tell whether the present deviation between the reference series and the ones derived from the structural patterns of the 1990s together with the latest KOF BTS data will remain, or whether the pending revisions of the official statistics will finally result in an OSF series which lies closer to these estimates than the present OSP series.

Charts 7 and 8 refer to the YTY growth rate of the incoming order index. Here, the very close correspondence between GR4ORDER and all its plotted estimations continues until 2002:1, the last observation of the (provisional) reference series, and there is no sign of a systematic deviation of either $g[BTS(t+u)]$ or $f[BTS(t)_t]$ from GR4ORDER in the out of sample period.

Moreover, both the OSP series and its estimations and forecast show a clear upward tendency beginning 2001:3/2001:4. Accordingly, there is some indication for an improvement of Swiss business conditions ahead, and – if nothing unforeseeable happens – a turning point of GR4PRODU can indeed be expected to occur during 2002, and the deviation of the provisional GR4PRODU and its latest estimations in charts 5 and 6 should not continue too far into the future.

Chart 7: Prediction of GR4ORDER (regressor set 1:
1st regressor with $|r|/\max$.)

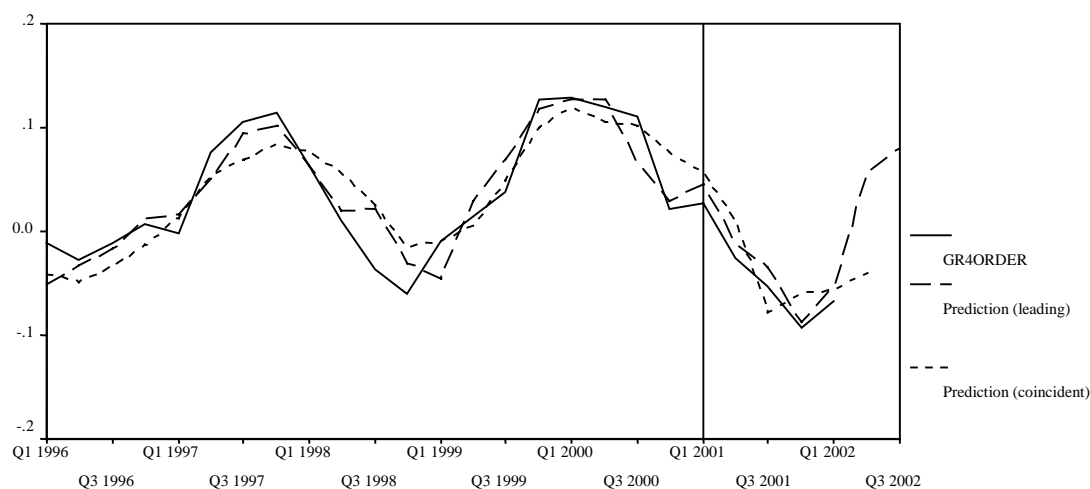
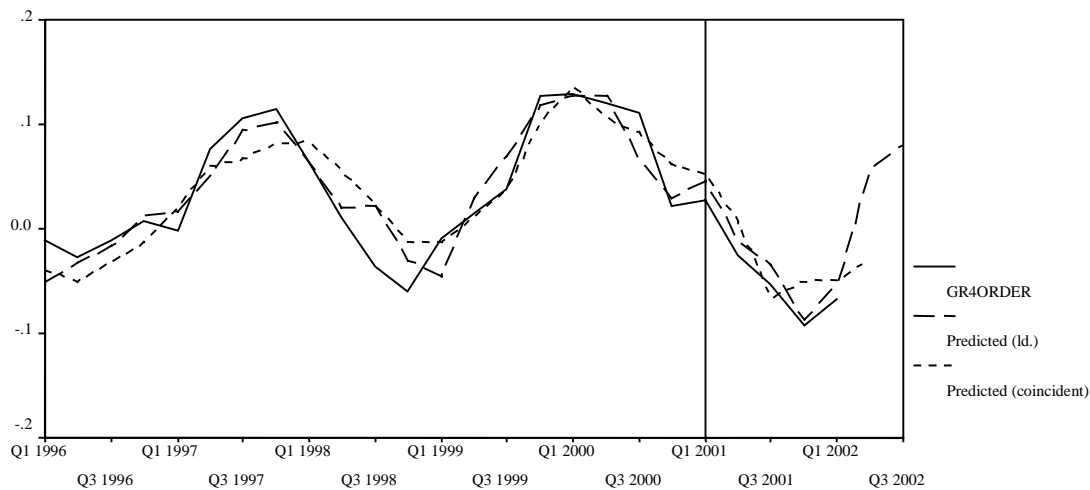


Chart 8: *Prediction of GR4ORDER (regressor set 2:
(1st regressor with best turning point properties)*



5 Conclusion

After a number of previous – disappointing – attempts by different researchers to derive indicators for Swiss official industrial statistics from BTS data, this study takes a new look at the data.

Our results from an extensive screening of the data are now reassuring with respect to the validity of both business survey data and industrial statistics for Switzerland on high levels of aggregation.

Specifically, for the 1990s, a reasonably close relationship was detected between a number of KOF BTS data and related official statistics for coincident series as well as for KOF BTS series with a lead of up to two quarters. Given this, the earlier availability of the survey data is clearly an advantage for policy oriented research.

Interestingly, when we use the structural parameters from the 1990s to compute out of sample estimates of the official SFSO production index series from 2001:1–2002:3, these estimates draw a somewhat more optimistic picture of present business conditions in Switzerland than the latest official – but still provisional – data.

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