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Short-Term Indicators: Using Qualitative Indicators to Update Production Indices

Paul Schreyer* and Corinne Emery*

Short-term economic indicators play an important role in the assessment of current cyclical situations and in the establishment of forecasts. Broadly, two types of short-term indicators can be distinguished: qualitative indicators, reflecting businessmen's subjective assessment of the cyclical situation (e.g., production prospects or judgements on orderbooks), and quantitative indicators, reflecting past developments of production or employment. The usefulness of qualitative indicators rests on their reliability to approximate the possible evolution of the quantitative ones.

The present document shows the results of a pilot study for six industrial sectors in seven Member countries whereby short-term qualitative indicators are used to "nowcast" a quantitative indicator, the production index. The objective is to enhance the timeliness of short-term industrial statistics through estimation of data points for the most recent periods for which they are not yet available.

From the current pilot project it emerges that: a) qualitative variables are clearly useful in forecasting indices of production; b) at the same time, they are not by themselves sufficient to provide good estimates of quantitative indices; c) the estimated time-series equations trace well the actual values of the production indices as comparisons of actual and fitted values for seven countries show; d) forecasting errors of the models are within reasonable bounds although there are clear differences across countries and sectors.

In conclusion, the project has shown the usefulness of qualitative variables and of the proposed methodology as a tool to provide timely estimates of short-term production indices.

Les indicateurs économiques à court terme jouent un rôle important dans l'appréciation des situations conjoncturelles et dans l'établissement des prévisions. On distingue en général deux types d'indicateurs à court terme : les indicateurs qualitatifs, qui reflètent l'opinion subjective des dirigeants d'entreprises sur la situation conjoncturelle (par exemple, les perspectives de production ou l'appréciation des carnets de commandes), et les indicateurs quantitatifs, qui rendent compte de l'évolution passée de la production ou de l'emploi. L'utilité des indicateurs qualitatifs repose sur leur capacité à anticiper avec fiabilité l'évolution possible des indicateurs quantitatifs.

Ce document présente les résultats d'une étude pilote concernant six secteurs industriels dans sept pays Membres, pour laquelle on utilise des indicateurs qualitatifs à court terme afin d'obtenir des prévisions instantanées d'un indicateur quantitatif, l'indice de production. L'objectif est d'améliorer le degré d'actualité des statistiques industrielles à court terme grâce à des estimations concernant les périodes les plus récentes pour lesquelles aucune donnée chiffrée n'est encore disponible.

Il ressort du projet pilote en cours que : a) les variables qualitatives sont de toute évidence utiles pour prévoir les indices de production ; b) par contre, elles ne suffisent pas, à elles seules, à fournir de bonnes estimations des indices quantitatifs ; c) les équations estimées retracent bien l'évolution effective des indices de production, comme le montrent les comparaisons effectuées pour sept pays entre les valeurs observées et les valeurs estimées ; d) les erreurs de prévision restent dans des limites raisonnables, malgré de nettes différences entre pays et entre secteurs.

En conclusion, le projet a montré l'utilité des variables qualitatives et de la méthodologie proposée pour estimer la valeur actuelle des indices de production à court terme.

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Introduction

Short-term economic indicators play an important role in the assessment of current cyclical situations and in the establishment of forecasts. Broadly, two types of short-term indicators can be distinguished: qualitative and quantitative ones. The former, although expressed in quantitative terms, typically reflect businessmen's subjective assessment of their specific or of the general cyclical situation. These assessments are normally in the form of answers to qualitative questions ("Will your production rise, fall or remain stable?") and so reflect an *ordinal* measurement. Typical qualitative indicators include production or employment prospects, judgements on orderbooks or stocks of finished products. Quantitative indicators, on the other hand, reflect developments with *cardinal* measurability, based on observations such as input use or physical output. Typical quantitative indicators are production and producer price indices or numbers of employees.

Much of the value of collecting qualitative indicators rests on the implicit assumption that those qualitative measures that deal with recent or future developments do actually reveal information about the future. In other words, qualitative indicators should have informational contents useful for forecasting, otherwise their value would be greatly reduced. There are, of course, good reasons to believe that businessmen, whose assessments are reflected in qualitative indicators, are good judges of recent or forthcoming developments in industry. Thus, from a statistical point of view, it seems reasonable to assume that observations of qualitative indices can be used as predictors for the development of quantitative indices.

The OECD Secretariat has, for a number of years, collected and published quantitative short-term indicators from its Member countries, both at the macro-economic *level (OECD Main Economic Indicators*) and at the sectoral level (OECD *Indicators of Industrial Activity*). In addition to quantitative indicators at the sectoral level, the *Indicators of Industrial Activity (IIA)* contain also several qualitative sectoral indicators. Both qualitative and quantitative short-term indicators in *IIA* are available as quarterly figures with time series that often cover two decades. As timeliness is one of the main advantages of short-term indicators, the Secretariat has continuously striven to reduce the lag between the date of observations and the date of publication, through improvements of data transmission and publication mechanisms. Yet, lags of at least one to two quarters remain. The Secretariat has therefore launched a pilot project to nowcast quantitative indicators where possible. The main feature of this nowcasting approach is the use of qualitative indicators, based on the above reasoning.

The present document presents this pilot project and its results for seven countries and six two-digit industries for each country. The document aims at responding to two, complementary objectives:

a) documentation of the usefulness of qualitative indicators collected for forecasting purposes;

b) provision of a tool to nowcast quantitative indicators of industrial activity to improve their timeliness.

Method

To show the usefulness of qualitative indicators for the forecasting of quantitative ones, a reliable econometric relation must be established between past observations of the former and current observations of the latter. The method chosen is essentially one of time-series analysis where, on purely statistical grounds, regularities are established either between two variables or between the current values of one variable and its past values. Thus, in its general form, the following type of relation was investigated econometrically. QUAN stands for the quantitative indicator, QUAL for the qualitative one:

$$QUAN_t = F(QUAN_{t-1}, \Lambda\ , QUAN_{t-n}, QUAL_{t-1}, \Lambda\ , QUAL_{t-m}) .$$

It should be noted that, unlike structural econometric models, time-series models do not generally reflect causal relationships or behavioural equations. This is also the case here where it clearly cannot be said that qualitative indicators actually "cause" the development of quantitative ones; however, it is assumed and will be demonstrated that the two vary closely with each other.

In the present pilot project, the index of industrial production was selected as the quantitative variable. For qualitative indicators, *IIA* offers a choice between several variables available: production prospects, judgements on stocks of finished goods, judgements on orderbooks, total order inflow, rate of capacity utilisation and labour force expectations. For economic reasons and to limit the number of estimates, only two qualitative variables were finally retained for estimation: production prospects and judgements on orderbooks. At the same time, these are the most widely available qualitative indicators. Still, at the sectoral level, qualitative data covers only the one- and two-digit industries and estimates had therefore to be confined to these sectors.

The estimation of the above relationship involves several practical issues.

a) availability of qualitative indicators is not ensured, simultaneously for all countries, all sectors and all types of indicators. For some countries, no qualitative indicators at all are available from the IIA data collection (e.g. for the United States where only private institutions collect qualitative variables but not the U.S. Government who supplies OECD with data) or data is only available for certain sectors. In the absence of qualitative data, estimation was based on a purely autoregressive process, involving only present and past observations of the quantitative variable:

$$QUAN_t = F(QUAN_{t-1}, \Lambda\ , QUAN_{t-n})$$

b) for particular sectors or countries, no significant relationship could be established between qualitative and quantitative variables. In this case also, a purely autoregressive approach was adopted.

In the current pilot study, seven diverse OECD Member countries were chosen (Japan, Canada, United States, Switzerland, Spain, Norway, and Sweden) and estimates carried out for six manufacturing industries (total manufacturing, textiles, paper, chemical industry, non-metallic minerals and basic metal industries). For each of the 42 cases, the specific form of the general equation had to be found using statistical criteria. The choice between conflicting specifications was based on considerations of goodness of fit and, more important, on the forecasting quality of the equation.

Goodness of fit was assessed by comparing how well the model chosen was able to trace actual developments of the past. Forecasting quality of estimates was evaluated through *ex-post forecasts*. Ex-post forecasts are generated by ignoring the latest realisation(s) of the quantitative variable in the estimation process and "forecasts" are then generated for these latest period(s). These *ex-post forecasts* can be compared with the actual value of the variable. The difference between the two provides a measure of the average forecasting error. Further details about the specification and estimation procedure as well as about the various tests applied can be found in a separate methodological paper that is available upon request from the Secretariat.

Results and conclusions

The following conclusions emerge from the current pilot study to nowcast the index of industrial production of six industries in seven countries:

a) **Qualitative variables are clearly useful in forecasting indices of production**. Their integration in models improved the goodness of fit and reduced forecasting errors. Little surprising, among the qualitative variables at hand, the ones representing "production prospects" and "judgements on orderbooks" were the most pertinent. However, the predictive capacity and significance of the qualitative variables differs significantly between countries (see Tables 1 to 7).

b) While useful in the estimation procedure, **qualitative indicators are not in general by themselves sufficient to provide good estimates of production indices**. Only in conjunction with past values of the production indices do most equations turn out to be of reasonable quality.

c) In those cases where qualitative variables do not improve forecasts of the quantitative ones**, no direct conclusions should be drawn concerning the quality of the underlying assessments of the business sector --** the type of questions posed and the way in which answers are translated into aggregate indicators may well be at the root of reduced predictive capacity of the qualitative variables.

d) Generally**, the final equations chosen trace well the actual values of the production indices**. This is visualised in Figure 1 and Figure 2, which show actual and fitted values for total manufacturing and the basic metal industry of six countries.

e) **Forecasting errors of the models are within reasonable bounds although there are clear differences across countries and sectors**. Table 1 shows the absolute percentage error of one-period forecasts for each country and sector. This measure compares predictions by the model with the actual realisation of the production index for the first quarter of 1995. It should be noted that this measure states the percentage difference in the level of the production index for a particular period. The error does not directly indicate the difference in growth rates which is a more pertinent measure of short-term developments.

Figure 1 Production index, actual and fitted values: total manufacturing

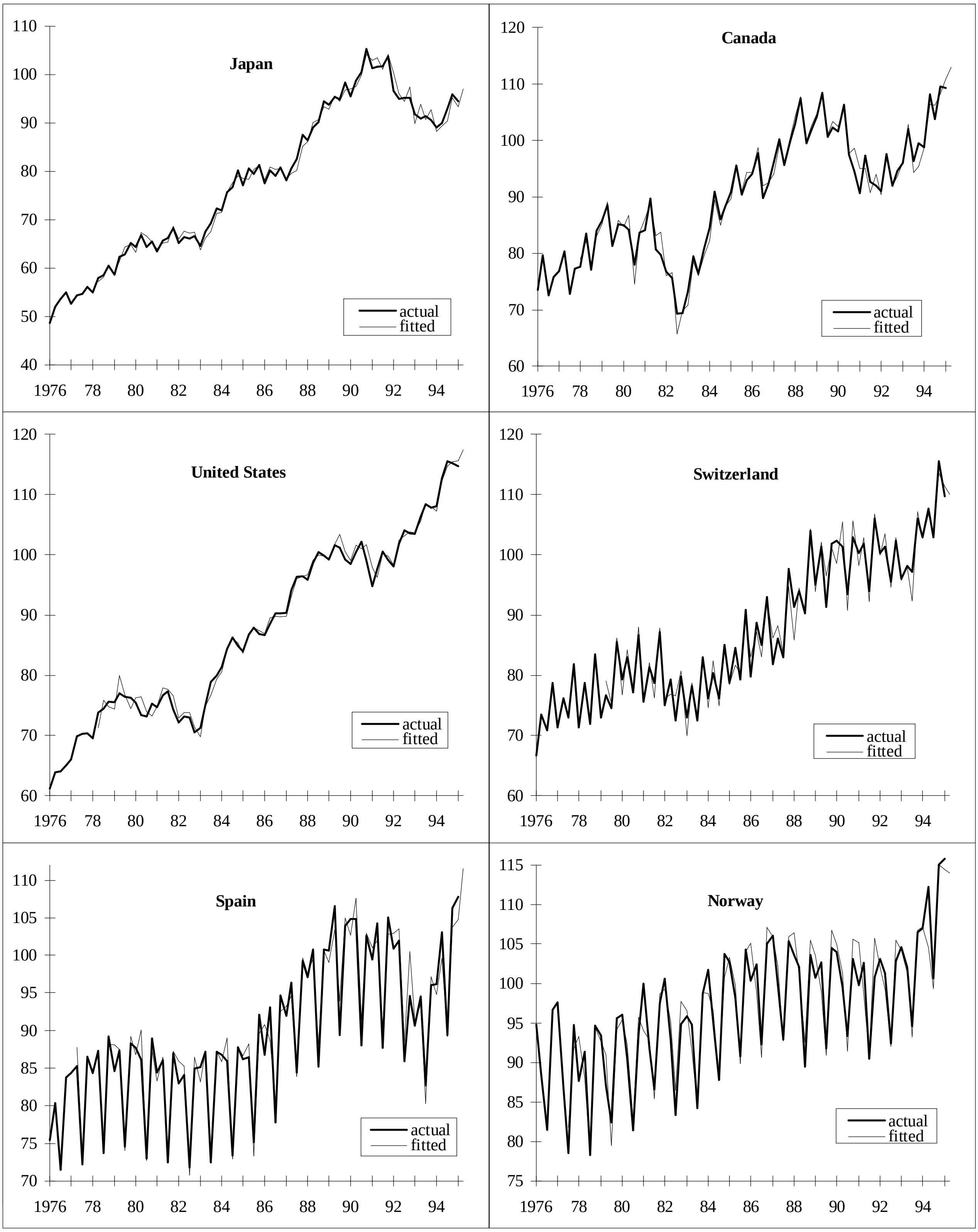

Figure 2 Production index, actual and fitted values:
basic metals industry

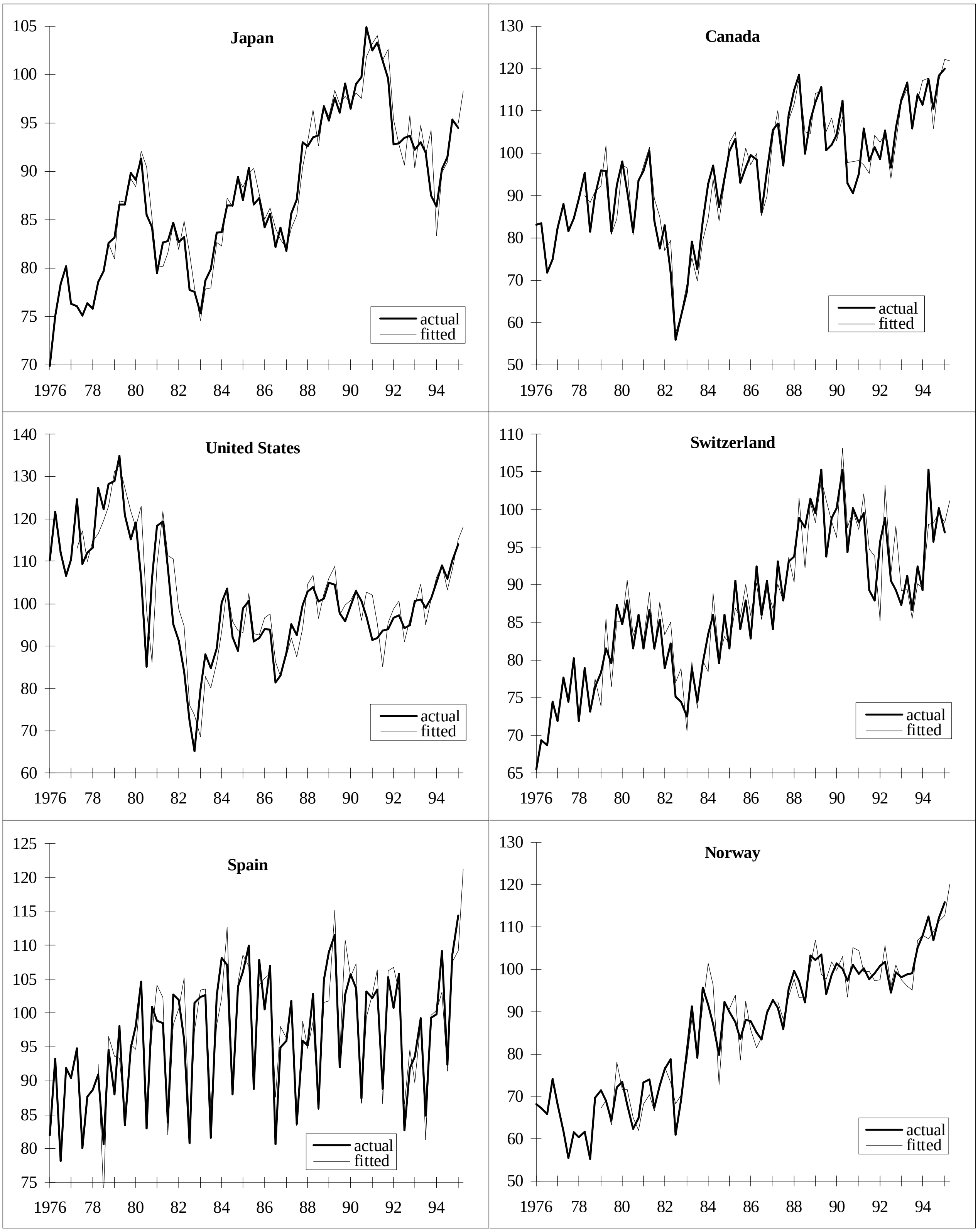

Table 1 Comparison between forecasts and realisation
1st quarter 1995

	Fitted value	Actual value	Absolute deviation (%)
Japan			
Manufacturing Industries	93.3	94.4	1.2
Textiles	76.6	75.0	2.1
Paper	101.9	101.3	0.6
Chemicals	105.4	105.4	0.0
Non-Metallic Mineral	93.4	92.9	0.6
Basic Metals	95.2	94.5	0.8
Canada			
Manufacturing Industries	110.9	109.2	1.5
Textiles	104.6	104.6	0.0
Paper	93.4	91.4	2.2
Chemicals	108.7	111.1	2.2
Non-Metallic Mineral	73.0	70.3	3.8
Basic Metals	122.8	119.9	2.4
United States			
Manufacturing Industries	115.8	114.7	0.9
Textiles	106.5	104.8	1.6
Paper	103.7	103.5	0.2
Chemicals	113.9	114.7	0.7
Non-Metallic Mineral	103.0	102.9	0.1
Basic Metals	115.2	114.1	1.0
Switzerland			
Manufacturing Industries	111.6	109.7	1.7
Textiles	99.0	102.6	3.5
Paper	106.6	108.5	1.7
Chemicals	142.8	146.4	2.5
Non-Metallic Mineral	73.5	78.3	6.1
Basic Metals	98.5	97.0	1.6
Spain			
Manufacturing Industries	104.6	107.8	2.9
Textiles	91.3	93.5	2.3
Paper	111.6	112.2	0.6
Chemicals	116.3	118.7	2.0
Non-Metallic Mineral	100.7	102.1	1.4
Basic Metals	108.3	114.4	5.3
Norway			
Manufacturing Industries	114.3	115.8	1.2
Textiles	114.9	117.4	2.1
Paper	113.4	114.5	1.0
Chemicals	107.5	111.6	3.7
Non-Metallic Mineral	112.8	115.7	2.6
Basic Metals	112.6	115.9	2.8
Sweden			
Manufacturing Industries	110.8	115.1	3.8
Textiles	74.3	78.6	5.5
Paper	100.9	100.4	0.5
Chemicals	118.5	123.9	4.3
Non-Metallic Mineral	80.8	72.9	10.8
Basic Metals	126.0	119.6	5.3

Table 2 Regression results: Canada

Explanatory variables	3 Manufacturing Industries	32 Textiles	34 Paper	35 Chemicals	36 Non-Metallic Mineral	37 Basic Metals
	Dependent variable: Index of Production (IP_t) (1)					
	Sector (ISIC Rev. 2)					
C (2)	0.024	0.098	-0.139	0.096	0.029	0.048
IP(t-1) (1)		-0.235	-0.235			
IP(t-3)		-0.355	-0.281			
IP(t-4)		-0.576	-0.225	-0.316	-0.785	-0.702
IP(t-8)				0.330		
PP(t-1) (3)	0.098	0.171	0.131			0.045
PP(t-4)	-0.044	-0.085				
PP(t-5)		0.119				
PP(t-7)		-0.091				
PF(t-3) (4)			0.042			
PF(t-4)				0.028		
MA(4) (5)	-0.591		-0.915			
MA(8)				-0.923	-0.948	-0.896
R^2	0.64	0.71	0.72	0.50	0.56	0.62
SEE	1.70	2.69	1.95	2.27	4.13	4.01
DW	1.89	2.26	2.09	1.79	1.45	1.84

Notes :

All the coefficients are significant at the 5% level.
(1) : Index of Production (time t)
(2) : Constant term
(3) : Production Prospects (time t-1)
(4) : Judgements on stocks of finished goods (time t-3)
(5) : Moving Average

Table 3 Regression results: Japan

Explanatory variables	3 Manufacturing Industries	32 Textiles	34 Paper	35 Chemicals	36 Non-Metallic Mineral	37 Basic Metals
	Dependent variable: Index of Production (IPt) (1)					
	Sector (ISIC Rev. 2)					
C [(2)]	-0.045	-0.133	0.092	0.013	0.037	0.033
IP(t-1) [(1)]	0.368			0.175	0.336	0.394
IP(t-3)			-0.339			
IP(t-4)	-0.411		-0.571	-0.711		
IP(t-5)		-0.300	-0.265			
CC(t-1) [(3)]			0.025			
CC(t-5)		-0.009				
CC(t-7)						-0.010
PF(t-6) [(4)]					0.037	
MA(4) [(5)]		-0.539			-0.946	-0.962
MA(8)	-0.829		-0.907	-0.867		
R^2	0.41	0.31	0.43	0.41	0.59	0.63
SEE	1.32	1.22	1.30	1.57	1.27	1.88
DW	2.00	1.71	1.85	2.01	2.16	1.98

Notes :

All the coefficients are significant at the 5% level.
(1) : Index of Production (time t)
(2) : Constant term
(3) : Production Prospects (time t-1)
(4) : Judgements on stocks of finished goods (time t-1)
(5) : Moving Average

Table 4 Regression results: Norway

	Dependent variable: Index of Production (IPt) (1)					
	Sector (ISIC Rev. 2)					
	3	32	34	35	36	37
Explanatory variables	Manufacturing Industries	Textiles	Paper	Chemicals	Non-Metallic Mineral	Basic Metals
C [(2)]	0.050	0.844	0.034	-0.045	0.227	0.293
IP(t-1) [(1)]	-0.504	-0.644	-0.484	-0.532	-0.501	
IP(t-2)		-0.222				
IP(t-4)		-0.349				-0.479
IP(t-5)						-0.271
PP(t-1) [(3)]					0.086	0.086
PP(t-2)						-0.056
PP(t-5)						0.055
PF(t-1) [(4)]		-0.184			-0.056	
PF(t-8)						0.035
MA(4) [(5)]	-0.904		-0.942	-0.937	-0.905	
R^2	0.66	0.66	0.61	0.52	0.54	0.46
SEE	2.59	6.06	2.27	3.73	4.84	3.86
DW	2.38	1.67	1.96	1.97	2.04	2.33

Notes :

All the coefficients are significant at the 5% level.
(1) : Index of Production (time t)
(2) : Constant term
(3) : Production Prospects (time t-1)
(4) : Judgements on stocks of finished goods (time t-1)
(5) : Moving Average

Table 5 Regression results: Spain

Explanatory variables	3 Manufacturing Industries	32 Textiles	34 Paper	35 Chemicals	36 Non-Metallic Mineral	37 Basic Metals
	Dependent variable: Index of Production (IPt) (1) — Sector (ISIC Rev. 2)					
C [(2)]	0.005	-0.005	0.006	0.071	0.136	0.002
IP(t-1) [(1)]		-0.228				
IP(t-4)		-0.614	-0.539	-0.578	-0.513	-0.517
IP(t-8)			-0.363			
PP(t-1) [(3)]	0.040					0.064
PP(t-6)				-0.061		
PF(t-1) [(4)]		-0.154				
MA(4) [(5)]	-0.899					
MA(8)				-0.881	-0.880	-0.859
R^2	0.45	0.41	0.27	0.49	0.40	0.46
SEE	2.12	4.52	4.05	2.32	2.65	3.70
DW	2.27	2.23	2.37	2.10	1.61	2.23

Notes :

All the coefficients are significant at the 5% level.
(1) : Index of Production (time t)
(2) : Constant term
(3) : Production Prospects (time t-1)
(4) : Judgements on stocks of finished goods (time t-1)
(5) : Moving Average

Table 6 Regression results: Sweden

Explanatory variables	Dependent variable: Index of Production (IPt) (1)					
	Sector (ISIC Rev. 2)					
	3	32	34	35	36	37
	Manufacturing Industries	Textiles	Paper	Chemicals	Non-Metallic Mineral	Basic Metals
C (2)	0.246	0.111	-0.017	0.193	0.164	0.098
IP(t-1) (1)	-0.569	-0.601	-0.560	-0.386	-0.265	
IP(t-2)		-0.308				
IP(t-4)	-0.327			-0.322	-0.459	
IP(t-6)		-0.255				
IP(t-7)		-0.282				
IP(t-8)				-0.257		
PP(t-1) (3)	0.145					
PP(t-2)						0.054
PP(t-3)		0.111				-0.073
PF(t-1) (4)			-0.042			-0.127
PF(t-2)	0.092				-0.149	0.141
PF(t-3)					0.106	
PF(t-5)	-0.201					
PF(t-6)	0.140		0.033			
MA(4) (5)		-0.745	-0.930			
R^2	0.42	0.54	0.51	0.32	0.35	0.35
SEE	2.54	5.49	2.53	3.66	5.75	5.02
DW	2.19	2.10	1.99	2.29	2.00	2.24

Notes :

All the coefficients are significant at the 5% level.
(1) : Index of Production (time t)
(2) : Constant term
(3) : Production Prospects (time t-1)
(4) : Judgements on stocks of finished goods (time t-1)
(5) : Moving Average

Table 7 Regression results: Switzerland

	Dependent variable: Index of Production (IPt) (1)					
	Sector (ISIC Rev. 2)					
	3	32	34	35	36	37
Explanatory variables	Manufacturing Industries	Textiles	Paper	Chemicals	Non-Metallic Mineral	Basic Metals
C (2)	0.061	0.123	0.016	0.301	0.224	-0.063
IP(t-1) (1)		-0.328	-0.397		-0.421	
IP(t-2)	-0.400			-0.261	-0.399	
IP(t-4)	-0.508	-0.307		-0.497	-0.353	-0.853
IP(t-5)						-0.182
IP(t-6)	-0.235					
IP(t-8)	-0.475					
PP(t-1) (3)	0.184				0.067	
PP(t-3)	-0.203					
PP(t-4)	0.117					
PF(t-1) (4)		-0.079		-0.048		
PF(t-3)				0.059		
PF(t-4)	-0.123	0.130		-0.063		
PF(t-5)		-0.152				
PF(t-6)	0.239					
PF(t-7)	-0.203					
MA(4) (5)			-0.899			
MA(8)						-0.876
R2	0.59	0.44	0.38	0.35	0.38	0.45
SEE	2.30	3.49	2.33	3.67	5.58	3.26
DW	2.41	2.05	1.90	2.16	2.10	2.38

Notes :

All the coefficients are significant at the 5% level.
(1) : Index of Production (time t)
(2) : Constant term
(3) : Production Prospects (time t-1)
(4) : Judgements on stocks of finished goods (time t-1)
(5) : Moving Average

Table 8 Regression results: United States

	Dependent variable: Index of Production (IPt) (1)					
	Sector (ISIC Rev. 2)					
	3	32	34	35	36	37
Explanatory variables	Manufacturing Industries	Textiles	Paper	Chemicals	Non-Metallic Mineral	Basic Metals
C (2)	0.068	-0.006	-0.021	0.026	-0.044	0.127
IP(t-1) (1)	0.283	0.270		0.482	0.269	
IP(t-2)				-0.239		
IP(t-4)	-0.689	-0.670	-0.711	-0.383	-0.476	
IP(t-8)		-0.288				
MA(4) (3)						-0.962
MA(8)	-0.925		-0.949			
R^2	0.53	0.49	0.42	0.40	0.31	0.47
SEE	1.20	1.97	1.11	1.50	2.69	6.23
DW	1.74	1.55	1.80	1.84	1.98	1.64

Notes :

All the coefficients are significant at the 5% level.
(1) : Index of Production (time t)
(2) : Constant term
(3) : Moving Average

TECHNICAL ANNEX: DESCRIPTION OF ESTIMATION PROCEDURES

This technical annex describes, in greater detail, the different steps and statistical procedures applied to *nowcast* indices of production of six manufacturing industries for seven OECD Member countries1. In its most general form, the following type of relation was investigated econometrically. QUAN stands for the quantitative indicator (index of production), QUAL for the qualitative one (production prospects or judgement on orderbooks):

$$QUAN_t = F(QUAN_{t-1},\ldots, QUAN_{t-n}, QUAL_{t-1},\ldots, QUAL_{t-m}) .$$

This approach falls in the class of autoregressive models with an exogenous variable (ARX) or ARMAX, depending on the inclusion of a moving-average term. The estimation procedure comprised three principal steps: (a) determination of the order of the process; (b) choice of the qualitative variable; (c) search for the final specification.

As all of the time series involved exhibited strong seasonal variations, and many variables trends, a fourth- and a first order differencing was carried out to obtain stationarity of the series. The source of all series are the *OECD Indicators of Industrial Activity* which permitted to construct coherent time series with observations starting in the early 1970s.

Determining the order of the ARX process

To determine the number of lags with which the qualitative exogenous variable QUAL enters the process, the ARX model is transformed into the more general form of a vector autoregressive (VAR) process. Transformation into a VAR model permits the use of the Akaike's Information Criterion (AIC) and Schwarz's Criterion (SC) to determine the order *p* of a VAR process. In VAR form, the model becomes:

$y_t = \sum_{i=1}^{p} \Theta_i y_{t-i} + v_t$ with $y_t = \begin{bmatrix} QUAN_t \\ QUAL_t \end{bmatrix}$; $v_t = (v_1, v_2)'$, and $\Theta_i = \begin{bmatrix} \theta_{11,i} & \theta_{12,i} \\ \theta_{21,i} & \theta_{22,i} \end{bmatrix}$, where Θ_i are coefficient matrices and v_1 and v_2 white noise error terms. The order of this VAR process is chosen so that AIC or SC are minimised. AIC and SC are defined as[1]:

$$AIC(n) = \ln\det(\tilde{\Sigma}_n) + \frac{2M^2 n}{T} \quad \text{and} \quad SC(n) = \ln\det(\tilde{\Sigma}_n) + \frac{M^2 n \ln T}{T},$$

where *M* is the number of variables in the system (*M=2* in the present case), *T* is the sample size and $\tilde{\Sigma}_n$ is an estimate of the residual covariance matrix obtained with a VAR(*n*) model. A prespecified upper bound P for the order of the model is set (P=8 in the present case) and models with order *n=1, 2,..P* are successively estimated. Then the criteria AIC and SC are computed with a fixed sample size *T*. The value *p(AIC)* is the order that minimises AIC over *n=1, 2,..P* and *p(SC)* is the order that minimises SC over *n=1, 2,..P*. In most cases, the two criteria produced the same optimal order. Whenever *p(AIC)* was different from *p(SC)*, the larger order was chosen.

Choice of the qualitative variable

In a second step, the VAR(p) formulation of the model was used to test whether, from a statistical viewpoint, the qualitative variables were useful predictors for the quantitative one and if so, which qualitative variable should be included in the specification. As a test for the inclusion of qualitative variable a Granger causality test was applied. The quantitative variable *QUAN* is said to be Granger-caused by the qualitative variable *QUAL*, if the information in past and present *QUAL* helps to improve the forecasts of the quantitative variable[2]. More formally, a Granger test involves restrictions on the coefficients Θ: *QUAL* does not Granger cause *QUAN* if and only if $\theta_{12,1} = \theta_{12,2} = \ldots = \theta_{12,p} = 0$. This hypothesis can be subjected to an F-test. Results of this test are presented in Annex Table 1.

Choice of the final specification

The third step in the estimation procedure involved the search for a final specification of each equation. Based on steps 1 and 2, different specifications were tested for each country and each industry. Only those qualitative variables that had passed the Granger causality test were considered. In the absence of a qualitative variable (because it did not pass the Granger causality test or because no qualitative variable was available), a purely autoregressive model was fitted. More specifically, the following procedure was followed:

First, all variables were entered into the equation with the optimal lag p(AIC) or p(SC): $QUAN_t = \sum_{i=1}^{p} \theta_i QUAN_{t-i} + \sum_{i=1}^{p} \vartheta_i QUAL_{t-i} + v_t$. Coefficients were estimated using ordinary least squares and only retained if they were significant at the 5 percent level. The eventual specification involved a case-by-case judgement of the goodness of fit.

Second, a Chow test (n-step forecast test) was run to test for misspecification.

Third, alternative specifications with a moving average specification of the error term (order 4 and order 8) were also routinely tried. For reasons of simplicity and because the inclusion of moving average terms involves non-linear estimation procedures, moving average terms were only retained if they significantly improved the goodness of fit and the mean square error of forecasts generated with the equation. To evaluate mean square errors of forecasts, the equations were re-estimated using a sample that excluded the latest four quarterly observations. The re-estimated equations allowed to carry out an ex-post forecast for these four quarters and compare it with the actual values.

Annex Table 1 Granger causality tests, probabilities[1]

Percentages

		PP [2]	IP [3]	JFG[4]	IP[5]
Canada	Manufacturing Industries	0.0	18.8	3.3	61.7
	Textiles	0.0	23.9	34.2	95.3
	Paper	0.0	32.2	0.2	0.5
	Chemicals	0.1	12.8	4.4	3.3
	Non-Metallic Mineral	3.1	23.1	56.0	15.6
	Basic Metals	0.2	13.6	84.4	2.7
Switzerland	Manufacturing Industries	0.8	33.9	3.1	43.1
	Textiles	7.8	24.4	0.1	11.7
	Paper	25.4	32.7	35.1	4.6
	Chemicals	67.6	42.2	7.4	4.6
	Non-Metallic Mineral	8.5	83.5	12.8	20.8
Spain	Manufacturing Industries	89.5	2.7	73.1	76.5
	Textiles	1.9	16.7	6.8	42.0
	Paper	10.1	5.0	62.0	50.7
	Chemicals	41.0	13.1	50.7	12.7
	Non-Metallic Mineral	14.2	79.1	59.7	4.7
	Basic Metals	0.5	67.7	26.5	2.9
Norway	Manufacturing Industries	47.1	84.3	16.9	20.4
	Textiles	0.2	4.3	0.1	25.1
	Paper	8.2	7.7	34.1	4.9
	Chemicals	86.1	23.8	55.4	29.3
	Non-Metallic Mineral	2.4	76.9	8.6	40.6
	Basic Metals	1.9	3.1	2.1	63.5
Sweden	Manufacturing Industries	0.5	13.3	0.3	15.4
	Textiles	2.6	28.6	13.5	4.3
	Paper	11.5	21.4	8.6	41.1
	Chemicals	0.1	14.5	13.6	63.7
	Non-Metallic Mineral	3.1	64.5	0.9	27.7
	Basic Metals	3.6	52.0	0.2	16.2
Japan		JO [6]	IP	JFG	IP
	Manufacturing Industries	37.7	1.0	89.9	0.0
	Textiles	0.8	3.5	15.2	11.5
	Paper	4.5	0.1	43.7	0.0
	Chemicals	75.4	1.7	66.0	0.4
	Non-Metallic Mineral	49.5	1.3	0.4	8.9
	Basic Metals	12.4	0.0	21.0	0.0

1. Test of hypotheses H_0: "The qualitative variable (PP, JFG, or JO) does not Granger-cause the quantitative variable IP" and "The quantitative variable IP does not Granger-cause the qualitative variables (PP, JFG or JO)". A low probability value leads to the rejection of H_0.
2. H_0: "Production prospects (PP) do not Granger-cause industrial production (IP)".
3. H_0: "Industrial production (IP) does not Granger-cause production prospects (PP)".
4. H_0: "Judgements on stocks of finished goods (JFG) do not Granger-cause industrial production (IP)".
5. H_0: "Industrial production (IP) does not Granger-cause judgements on stocks of finished goods (JFG)".
6. H_0: "Judgements on orderbooks (JO) do not Granger-cause industrial production (IP)".

Source: OECD, EAS Division.

NOTES

[1] Judge, G., R.C. Hill, W.E. Griffiths, H. Lütkepohl, T. Lee (1988), *Introduction to the Theory and Practice of Econometrics*, New York.

[2] The quantitative variable can Granger-cause the qualitative variable if expectations and assessments of the business sector are formed on the basis of recent realisations of the quantitative variable

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