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by

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Abstract

The paper investigates the usefulness of quantitative and qualitative indicator variables as forecasting means of industrial production growth in France, Germany, and Italy. The analysis is carried out for two sets of forecasts whose main difference concerns the way in which projections are defined. Forecasts are obtained from simultaneous equations models that generate predictions from the autoregressive processes of indicator variables. In computing root mean squared error statistics and Theil inequality coefficients, the forecasting performance of the leading indicators is compared against forecasts from the autoregressive structure of the reference series. The empirical evidence points to the usefulness of the sampled indicator variables as forecasting instruments of industrial production growth. Dependent on the set of forecasts, satisfactory predictions are available for the short- or medium-run, i.e., for the period of one month or for the horizon of three- to six-months.

Keywords: Business Cycles, Leading Indicators, Forecasting
JEL Classification: E32, E37, C22

I. Introduction

The decision-making process of policy-makers and business entities is guided by expectations as to the future state of the economy. In order to gain a view on the possible stance of the future economic performance, indicator variables are required which establish a stable lead over the business cycle. The need for leading indicators is particularly apparent for the Euro-zone countries whose performance is increasingly determined by economic policies that adopt a European focus. The change in the geographic scope of applicability of economic policies imposes new demands on the properties that appropriate indicator variables should possess. They are not only required to account for country-specific features of economic structures, but have to represent structures common to the EMU member countries as well.

Numerous studies aim at identifying indicator variables which lead the business cycle of individual countries as well as of the Euro-zone. Differing in terms of focus and methodology, studies in this field are presented by Fritsche and Stephan (2000), Bandholz and Funke (2001), Fritsche and Marklein (2001), Mourougane and Roma (2002), and Raabe (2002). While the first two studies explore the leading properties of indicator variables for the German business cycle, the third study identifies leading indicators for the reference series of the Euro-zone business cycle. The fourth and fifth study adopt an international comparative focus. While Raabe (2002) discusses the lead characteristics of indicators for France, Germany, and Italy, Mourougane et al. (2002) also investigate Belgium, the Netherlands, and Spain.

These studies have in common that they provide evidence for the in-sample performance of indicator variables. In-sample investigations may give an incorrect account of the forecasting ability of indicator variables. With the exception of Raabe (2002), the above analyses are extended to also examine the out-of-sample predictive power of leading indicators from econometric models.[1] The results generally indicate that variables which lead business cycles in within-sample estimations fail to satisfactorily anticipate future cyclical fluctuations. In order to provide a complete picture on the lead properties of quantitative and qualitative indicator variables that lead the business cycle of France, Germany, and Italy in with-sample estimations, the purpose of this paper is to assess these variables' out-of-sample forecasting ability.

The remainder of the paper has the following structure. Section two reviews the existing empirical evidence on the in-sample and out-of-sample performance of leading indicator variables. Section three elaborates on the empirical framework. The fourth section reports the findings of the empirical analysis. The final section summarizes and concludes.

[1] Additional studies that only assess the in-sample performance of indicators are reported by, e.g., Stock and Watson (1998) and Nilsson (2000).

II. Existing Empirical Evidence

The search for leading indicators is motivated by their proclaimed significance as means of providing information on the future stance of the economy. In within-sample investigations, numerous empirical analyses provide evidence as to the ability of qualitative and quantitative variables to establish a lead over the reference series of the business cycle.

Employing similar estimation methodologies, Fritsche et al. (2000, 2001) investigate the leading properties of monetary and non-monetary variables. In Fritsche et al. (2000), the evidence points to the significance of the Ifo business climate index, order inflows, and the interest rate spread as leading indicators of industrial production growth. No relevance is assigned to the EC confidence indicator, the real effective exchange rate, and money supply. Fritsche et al. (2001) provide ambiguous support for these findings. While monetary aggregates do not qualify as indicator variables, survey indicators of the European Commission (EC) are suggested to exhibit satisfactory lead characteristics.

Bandholz and Funke (2001) and Mourougane and Roma (2002) present studies that investigate the leading indicator properties of either quantitative or qualitative variables, respectively. Adopting a dynamic common factor model, Bandholz et al. (2001) identify the index of new orders total manufacturing and the finished goods stock level as significant components of a composite index of leading indicators. Considering Mourougane et al. (2002), estimates from constant and time-variant parameter models point to the usefulness of EC confidence indicators as leading variables. With the exception of Spain, this result holds for all sampled countries.

Considering the in-sample investigation of Raabe (2002) for France, Germany, and Italy, variables that are commonly found to be related to the growth rate of the reference series are the consumer price index, the assessment of order book positions, production expectations, EC economic sentiment, industry confidence, and the OECD leading indicator. No significant linkages appear to run from construction confidence to the reference series of the business cycle. Cross-country dissimilarities exist with respect to the relevance of the share price index, retail trade confidence, and consumer confidence. While the relevance of the first two variables is particular to Italy, the significance of consumer confidence is specific to Germany.

Except for Raabe (2002), the above mentioned studies also investigate the quality of out-of-sample forecasts. Bandholz et al. (2001) investigate the forecasting performance of leading indicators by re-estimating in-sample models recursively. They conclude that the constructed composite index of leading indicators performs well in anticipating business cycle fluctuations.

Fritsche et al. (2000, 2001) adopt a two-stage forecasting methodology to test the out-of-sample forecasting performance of indicator variables. In a first step, they estimate vector-autoregressive (VAR) processes that consists of the reference series of the business cycle and leading indicators. These are employed to construct endogenous forecasts for the indicator variables. The second step involves the computation of forecast error statistics. In contrast to Bandholz et al. (2001), the leading indicators are found to exhibit poor forecasting qualities. Variables that establish a satisfactory lead over the business cycle only do so over a six-months forecast horizon.

Similar to Fritsche et al. (2000, 2001), Mourougane et al. (2002) employ a two-stage forecasting approach to assess the out-of-sample forecasting performance of indicator variables. The first step consists of the estimation of an ARIMA-model that accounts for the underlying structure of the reference variable. This model is used as a benchmark against which the quality of forecasts from constant and time-variant parameter models is judged. The second step involves the computation of the relative mean squared forecasting error.[2] Considering the results, the EC confidence indicators exhibit a satisfactory one-month ahead out-of-sample forecasting performance in all countries, except Spain.

The current paper is in the style of Fritsche et al. (2000, 2001) and Mourougane et al. (2002). The similarity in the approach concerns the use of VAR models as forecasting framework and the application of the root mean squared error and the Theil inequality coefficient as error statistics. One difference relates to the way in which forecasts are defined. The earlier analyses assess the out-of-sample performance of indicator variables by forecasting industrial production growth on a monthly basis. The current examination goes further in that it also reports the quality of out-of-sample forecasts that are constructed from the cumulative sum of monthly forecasts. Another disparity exists with respect to the countries for which forecasts are generated. In particular, the analysis is carried out for the three largest EMU member countries, i.e., France, Germany, and Italy. A detailed description of the empirical approach is given in the next section.

III. Empirical Framework

Forecasts of industrial production growth are derived by specifying a simultaneous equations model that generates predictions by forecasting the exogenous variables from their underlying autoregressive processes. In capturing the underlying empirical structure of exogenous

[2] The relative mean squared forecasting error is the ratio of the mean squared forecasting error of the constant or time-variant parameter models and the mean squared forecasting error of the ARIMA specification (Mourougane et al., 2002, p. 12).

variables, the dynamic framework assumes the form of a VAR model that consists of the business cycle's reference series, IP, and the indicator variables, LI.[3] For indicator variables which are integrated of order one, I(1), VAR models are specified for their first-difference. With industrial production containing a unit root, the test equation equals:

$$\text{(1a)}\qquad \begin{bmatrix} \ddot{A}IP_t \\ \Delta LI_t \end{bmatrix} = \begin{bmatrix} \acute{a}_1 \\ \acute{a}_2 \end{bmatrix} + \sum_{j=1}^{p} \left(\begin{bmatrix} \hat{a}_{11}^{(j)} & \hat{a}_{12}^{(j)} \\ \hat{a}_{21}^{(j)} & \hat{a}_{22}^{(j)} \end{bmatrix} \begin{bmatrix} \ddot{A}IP_{t-j} \\ \Delta LI_{t-j} \end{bmatrix} \right) + \begin{bmatrix} \mathring{a}_{1,t} \\ \mathring{a}_{2,t} \end{bmatrix}, \qquad \hat{a}_{21}^{(j)} = 0\,.$$

Δ depicts the difference operator of variable X defined by $\Delta X_t \equiv X_t - X_{t-1}$. For indicator variables that are level-stationary, VAR estimations are carried out according to the following specification:

$$\text{(1b)}\qquad \begin{bmatrix} \ddot{A}IP_t \\ LI_t \end{bmatrix} = \begin{bmatrix} \acute{a}_1 \\ \acute{a}_2 \end{bmatrix} + \sum_{j=1}^{p} \left(\begin{bmatrix} \hat{a}_{11}^{(j)} & \hat{a}_{12}^{(j)} \\ \hat{a}_{21}^{(j)} & \hat{a}_{22}^{(j)} \end{bmatrix} \begin{bmatrix} \ddot{A}IP_{t-j} \\ LI_{t-j} \end{bmatrix} \right) + \begin{bmatrix} \mathring{a}_{1,t} \\ \mathring{a}_{2,t} \end{bmatrix}, \qquad \hat{a}_{21}^{(j)} = 0\,.$$

In (1a) and (1b), $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are white noise error terms.

Besides computing out-of-sample predictions from the constructed VAR-models[4], forecasts are also generated from the autoregressive structure of the reference series. Equation (2) depicts the model that is derived by setting $\hat{a}_{12}^{(j)}$, $\hat{a}_{21}^{(j)}$, and $\hat{a}_{22}^{(j)}$ equal to zero in (1a) and (1b).

$$\text{(2)}\qquad \ddot{A}IP_t = \acute{a}_1 + \sum_{j=1}^{p} \hat{a}_j\, \ddot{A}IP_{t-j} + \mathring{a}_{1,t}\,.$$

In estimating this univariate 'naive' model, a benchmark is generated against which to judge the quality of predictions from the VAR specifications.

The structure of the VAR and AR models is determined within the framework of Granger-causality tests; the estimation results being reported in Raabe (2002).[5] Out-of-sample predictions are generated for the one-, three-, and six-months horizon, using a rolling sample of estimations from 1998:1 to 2001:8. For each time horizon, the discussion centers on two sets of forecasts. The first set (A) builds on x-months ahead predictions which are constructed

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[3] Alternatively stated, the vector-autoregressive systems as used here are identical to unidirectional Granger-causal test equations.

[4] As a reminder, the part of the VAR model that consists of the reference series and the indicator variable matches the structure of the Granger-causal test equations reported in Raabe (2002).

[5] The structure of the bi- and multivariate Granger-causality models is reported in Tables 3-5 and Table 7 in Raabe (2002).

by forecasting industrial production growth on a monthly basis x-times. The second set (B) consists of forecasts which are generated by predicting x-months ahead industrial production growth from the cumulative sum of x monthly forecasts.

Judgments as to the accuracy of forecasts are based on the root mean squared error (RMSE) statistic and the Theil inequality coefficient. The error statistics are computed for forecasts of the reference series' level. Being derived from projections of the growth rate, forecasts of the level of industrial production are formally expressed as:

$$\text{(3)} \qquad \hat{y}_{t+\tau|t} = y_t + \Delta\hat{y}_{t+\tau|t} + \Delta\hat{y}_{t+\tau-1|t} + \ldots + \Delta\hat{y}_{t+1|t},$$

where y_t and $\hat{y}_t$ are the actual and forecasted values of industrial production, respectively. The parameter τ depicts the forecast horizon, being equal to one, three, or six months. Subscript t is an index of the last period in the observed sample.

Taking into account the recursive nature of the estimation approach, the RMSE is formally expressed as:

$$\text{(4)} \qquad RMSE = \frac{1}{N}\left(\sum_{t=T+1}^{T+N} \sqrt{\frac{1}{h}\sum_{j=1}^{h}\left(\hat{y}_{t+j|t} - y_{t+j}\right)^2}\right).$$

According to this expression, forecasts are generated h steps ahead from time T for a time series of length N. The parameter h equals one, three, or six under forecasting set A, whereas it is unity under set B. Subscript t depicts the last period in the estimation sample.

The RMSE allows for the comparison of the models' forecasting performance across methods and time horizons. Since this statistic is a relative and scale-variant evaluation tool, it cannot be used to evaluate the quality of forecasts. To account for this aspect, the Theil inequality coefficient is computed according to:

$$\text{(5)} \qquad Theil = \frac{1}{N}\left(\sum_{t=T+1}^{T+N} \frac{\sqrt{\frac{1}{h}\sum_{j=1}^{h}\left(\hat{y}_{t+j|t} - y_{t+j}\right)^2}}{\sqrt{\frac{1}{h}\sum_{j=1}^{h}\left(\hat{y}_{t+j|t}\right)^2} + \sqrt{\frac{1}{h}\sum_{j=1}^{h}\left(y_{t+j|t}\right)^2}}\right).$$

Assuming values between zero and one, the forecasting performance of models deteriorates as the coefficient approaches unity.[6]

IV. Empirical Evidence

The study builds on monthly data to investigate the ability of quantitative and qualitative economic measures to lead industrial production for France, Germany, and Italy. Quantitative instruments are country-specific share price indices and consumer price indices. Qualitative variables are indicators on industry, construction, retail, and consumer confidence, the EC economic sentiment indicator, the OECD leading indicator, the assessment of the order book position, and production expectations.[7]

The empirical findings are examined along two lines. One line of investigation involves the identification of the time horizon for which forecasts exhibit the best fit. The second topic centers on the evaluation of the forecasting quality of the various indicator variables. Regardless of the analytical focus, the results are compared across error statistics and across the sampled countries. Table 1 and Table 2 display the RMSE statistic and the Theil inequality coefficients, respectively. In structuring the analysis, the results are first reported for forecasts from set A.

IV.1 Performance of Monthly Forecasts

Considering the optimum forecast horizon for predictions constructed by forecasting industrial production growth on a monthly basis, the conclusions vary with the choice of the error statistic. According to the RMSE, one-month ahead predictions fit actual industrial production growth best. While forecasts for the period of six-months are less accurate than those at the one-month horizon, they outperform three-months predictions. The ranking of the forecast horizons is similar for France, Germany, and Italy and does not vary with the choice of the indicator variable.

While the RMSE statistic consistently identifies one-month forecasts as the optimum forecast horizon, the Theil inequality coefficient suggests a different ranking. For France, predictions for the period of three months generally outperform those for the one- and six-months

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[6] Textbook expressions of the RMSE statistic and the Theil inequality coefficient are not specified for rolling sample estimations. Accordingly, the textbook formalization is the second term in brackets in (3) and (4).

[7] For a detailed description of the data set and unit root characteristics of the variables, see Raabe (2002). Appendix A.I elaborates on the notation and the source of the variables.

horizon. Comparing the quality of forecasts for the one- and six-months horizon, six-months projections fit actual industrial production growth better than one-month forecasts. With respect to Germany, six-months forecasts tend to be more accurate than one- and three-months ahead predictions. Whereas the choice of the error statistic clearly affects the ranking of the optimum forecast horizon for France and Germany, the results are more robust in the case of Italy. Similar to the RMSE statistic, the Theil inequality coefficient indicates that one-month ahead predictions fit actual industrial production growth best. Dependent on the indicator variable, the relative ordering of three- and six-months forecasts varies.

Contrasting the quality of forecasts across France, Germany, and Italy, the countries' relative ranking depends on the error statistic and the forecast horizon. Considering the three-months horizon, the RMSE and the Theil inequality coefficients allow for a similar ranking of France, Germany, and Italy. At this horizon, the error statistics are lower for France than for Italy or Germany. Since the data are equally scaled across countries, the evidence, hence, suggests that three-months forecasts for France outperform those for Germany and Italy. Evaluating the predictions for Germany and Italy, the forecasting ability is more satisfactory for the former than for the latter economy.

As regards the one- and six-months forecast horizon, the choice of the error statistic feeds back into the relative ordering of the countries. While the RMSE statistic of one- and six-months forecasts points to a ranking of the sampled countries similar to that at the three-months horizon, a different country ranking is suggested by the Theil coefficient. Indeed, this error statistic indicates that one-month forecasts for Italy are superior in terms of accuracy and reliability to those for France and Germany. The relative ordering of France and Germany differs across indicator variables. Turning to the six-months prognosis, forecasts for Germany outperform those for France. Across the sampled countries, six-months projections for Italy have the lowest predictive power.

Up to this point, the analysis assesses the estimation results without evaluating the forecasting performance of the indicator variables. Turning to the latter issue, the forecasting ability of indicator variables is examined by comparing the Theil inequality coefficients from bivariate and multivariate Granger-causal models with those from the univariate benchmark model. The analysis proceeds by first comparing the forecasts from the univariate and bivariate specifications.

As regards Germany, quantitative and qualitative indicator variables can anticipate industrial production growth better than past values of the reference series at all forecast horizons. In the case of France, similar conclusions apply to the forecasting ability of industry confidence, production expectations, and the consumer price index. Different to Germany, the assessment of the order book position and the indicators of the European Commission and the OECD only generate adequate three- and six-months forecasts.

With respect to Italy, forecasts from the consumer price index, retail trade confidence, and the indicators of the OECD and EC are more accurate than those constructed on the basis of the reference series' autoregressive structure at the investigated forecast horizons. Projections from industry confidence, production expectations, and the assessment of the order book position prove to be appropriate forecasting instruments at the one- and sixth-months horizon. The relevance of the share price index as forecasting instrument is limited to three- and six-months ahead predictions.

Comparing the quality of forecasts from univariate and multivariate model specifications, a group of indicator variables is found to be better able to accurately predict industrial production growth than are the past values of the reference series.[8] This empirical result applies to all time horizons. Predictions from multivariate models are not only more reliable than those from the benchmark model. Instead, they also tend to be more accurate than forecasts from bivariate model specifications. This finding points to the relevance of a composite index of leading indicators that can anticipate business cycle fluctuations better than individual time series.

IV.2 Performance of Aggregate Forecasts

Turning to forecasts constructed for the aggregate of x-months ahead industrial production growth, the choice of the error statistic again influences statements as to the optimal forecast horizon. According to the Theil inequality coefficient, six-months ahead forecasts are more reliable than those at the one- and three-months horizon and forecasts for the period of three months tend to outperform one-months predictions. The ranking of the forecast horizon is largely invariant across the indicator variables, being similar for France, Germany, and Italy.

The RMSE statistic hints at a different ranking. For France and Germany, three-months ahead projections outperform those at the one- and six-months horizon and six-months predictions fit industrial production growth better than one-month ahead forecasts. In the case of Italy, the relative ordering is not robust to the choice of the indicator variable. It appears, however, that the least accurate forecasts are those at the one-month horizon.

[8] This finding is derived for the countries' first-best multivariate model specification. The corresponding regression outputs are reported in Raabe (2002), Table 7.4 (France, Italy) and Table 7.5 (Germany).

Contrasting the quality of predictions across the sampled countries at the three- and six-months forecast horizon[9], the ranking of countries is largely invariant to the choice of the error statistic and to the choice of the indicator variable. Indeed, the RMSE statistic and the Theil inequality coefficient indicate that forecasts for France are more reliable than those for Italy and Germany. Predictions for Italy generally outperform those for Germany. Using the Theil inequality coefficient, deviations from this ordering arise at the three-months horizon. In particular, forecasts for Italy fit actual industrial production growth better than those for France and Germany, while predictions for France tend to outperform forecasts for Germany.

Similar to the previous analysis, the forecasting ability of indicator variables is examined by comparing the Theil coefficients from the bivariate and multivariate Granger-causal models with those from the univariate benchmark specification. Contrasting the univariate and bivariate estimation results, three- and six-months forecasts from indicator variables are generally more accurate than those from the autoregressive structure of industrial production in the case of Germany and Italy. For these economies, the corresponding exceptions are prognoses from retail trade confidence and consumer confidence. Considering France, projections from the univariate benchmark model fit actual production growth better than those from bivariate specifications. This result holds for all indicator variables at the three-months horizon, while it does not apply to the consumer price index and the OECD leading indicator at the six-months horizon.

Comparing the quality of forecasts from the benchmark specification and the multivariate model, forecasts from a group of indicator variables anticipate business cycle fluctuations better than those from the past values of the reference series. For Germany and Italy, this result holds at the three- and six-months horizon, while it is particular to the six-months horizon in the case of France. Confirming the earlier findings from monthly forecasts, multivariate frameworks again tend to account for more accurate predictions than bivariate model specifications.

[9] Since one-month forecasts in section IV.2 are identical to those in section IV.1, the analysis' focus is subsequently restricted to the three- and six-months horizon.

V. Synthesis and Conclusion

The analysis presented in this paper examines the out-of-sample forecasting ability of variables that prove to be able leading instruments in within-sample investigations for France, Germany, and Italy. Test statistics are reported for two sets of forecasts. The first set (A) generates x-months ahead predictions by forecasting industrial production growth on a monthly basis x-times. The second set (B) employs the cumulative sum of x monthly forecasts to predict x-months ahead industrial production growth. Forecasts from set A and B confirm the empirical findings from Granger-causality tests and error correction estimations in that forecasts from the benchmark model are generally less accurate than those from the bivariate and multivariate specifications. That is, the out-of-sample tests suggest that the sampled leading indicator variables are useful forecasting instruments.

Apart from this common finding, the quality of predictions differs across the two forecasting sets. These differences are mirrored in the results of the error statistics. Indeed, the RMSE and Theil inequality coefficients for France, Germany, and Italy indicate that forecasts from set B fit actual industrial production growth better than those from set A. Another difference concerns the length of the optimum forecast horizon. According to the RMSE statistic, predictions from set A display the best fit at the one-month horizon, while those from set B are the most suitable forecasting instruments at the three-months horizon. Interestingly, the optimum forecast horizon for set A is the worst-performing forecast horizon for set B, vice versa.

Investigating Theil inequality coefficients, forecasts from set B have the highest predictive power at the six-months horizon, while one-month ahead forecasts exhibit the poorest performance. Up to this point, the ranking of the optimum forecast horizons is largely similar for France, Germany, and Italy. Only the Theil coefficient from set A hints at the existence of cross-country differences. According to the corresponding estimations, projections from set A exhibit the best performance at the one-, three-, and six-months horizon for Italy, France, and Germany, respectively.

In summary, the length of the optimum forecast horizon is found to vary across error statistics and indicator variables, being also influenced by the way in which forecasts are defined. The estimation results indicate that predictions from set A are most satisfactory at the one-month horizon, while those from set B perform best at the three- and six-months horizon. The empirical findings, hence, corroborate the common believe and general empirical evidence of the short- to medium-run usefulness of forecasts.

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APPENDIX

A.I Variable Explanation

Variable	Units	Source[a]	Abbreviation	
			Level	First-Difference
Industrial Production Index	1995=100	OECD Main Economic Indicators	IP	Δ IP
Consumer Price Index	1995=100	OECD Main Economic Indicators	CPI	Δ CPI
OECD Leading Indicator	[b]	OECD Main Economic Indicators	OL	Δ OL
Economic Sentiment Indicator	1995=100	European Commission	ES	Δ ES
Share Price Index	1995=100	European Commission	SPI	Δ SPI
Order Book Position	% Balance	European Commission	OBP	Δ OBP
Production Expectations	% Balance	European Commission	PE	Δ PE
Industrial Confidence Indicator	% Balance	European Commission	CI	Δ CI
Construction Confidence Indicator	% Balance	European Commission	CC	Δ CC
Consumer Confidence Indicator	% Balance	European Commission	CK	Δ CK
Retail Confidence Indicator	% Balance	European Commission	CR	Δ CR

[a] The data are extracted from Datastream.

[b] Different base years.

A.II Empirical Results

- In all out-of-sample exercises, the endogenous variable is always the first log-difference of industrial production Δ IP.
- Set A builds on x-months ahead predictions which are constructed by forecasting industrial production growth on a monthly basis x-times.
- Set B consists of forecasts which are generated by predicting x-months ahead industrial production growth from the cumulative sum of x monthly forecasts.

Table 1 Root Mean Squared Error Statistic

Table 1.1 France

	Set A, Set B	Set A		Set B	
Exogenous Variable	**1-Month**	**3-Months**	**6-Months**	**3-Months**	**6-Months**
IP 1 [a]	.00423	.0204	.0162	.00375	.00415
IP 2 [b]	.00431	.0200	.0157	.00373	.00409
CI	.00502	.0205	.0160	.00431	.00437
PE	.00498	.0226	.0169	.00467	.00485
OBP	.00544	.0187	.0143	.00460	.00498
D **CPI**	.00470	.0203	.0156	.00386	.00363
D **ES**	.00501	.0184	.0151	.00412	.00412
D **OL**	.00541	.0208	.0161	.00473	.00519
Multivariate [c]	.00606	.0191	.0163	.00410	.00395

[a] Univariate Model 1 : $ÄIP_t = á_1 + â_1 ÄIP_{t-1} + â_2 ÄIP_{t-2} + å_{1,t}$.

[b] Univariate Model 2 : $ÄIP_t = á_1 + â_1 ÄIP_{t-1} + â_2 ÄIP_{t-3} + å_{1,t}$.

[c] Multivariate Model :

$$ÄIP_t = á_1 + \sum_{j=1}^{j=2} \beta_i \Delta IP_{t-j} + \sum_{j=1}^{j=10} \gamma_i \Delta CPI_{t-j} + \sum_{j=1}^{j=5} \delta_i \Delta OL_{t-j} +$$

$$+ \sum_{j=1}^{j=7} \phi_i \Delta ES_{t-j} + \sum_{j=1}^{j=8} \varphi_i OBP_{t-j} + \sum_{j=1}^{j=7} \theta_i PE_{t-j} + å_{1,t} .$$

Table 1.2 Germany

	Set A, Set B	Set A		Set B	
Exogenous Variable	**1-Month**	**3-Months**	**6-Months**	**3-Months**	**6-Months**
IP [a]	.00857	.0254	.0206	.00709	.00802
CI	.00820	.0258	.0202	.00625	.00706
PE	.00806	.0253	.0201	.00676	.00764
OBP	.00820	.0261	.0204	.00674	.00738
D **CK**	.00856	.0265	.0200	.00752	.00811
D **CPI**	.00831	.0269	.0210	.00683	.00697
D **ES**	.00882	.0254	.0201	.00654	.00750
D **OL**	.00814	.0247	.0209	.00581	.00575
Multivariate [b]	.00746	.0252	.01981	.00523	.00606

[a] Univariate Model : $\Delta IP_t = \alpha_1 + \beta_1 \Delta IP_{t-1} + \beta_2 \Delta IP_{t-2} + \varepsilon_{1,t}$.

[b] Multivariate Model : $\Delta IP_t = \alpha_1 + \sum_{j=1}^{j=2} \beta_i \Delta IP_{t-j} + \sum_{j=1}^{j=10} \gamma_i \Delta CPI_{t-j} + \sum_{j=1}^{j=2} \delta_i \Delta OL_{t-j} +$

$$+ \sum_{j=1}^{j=3} \phi_i CI_{t-j} + \sum_{j=1}^{j=3} \varphi_i OBP_{t-j} + \sum_{j=1}^{j=8} \theta_i PE_{t-j} + \varepsilon_{1,t} .$$

Table 1.3 Italy

	Set A, Set B	Set A		Set B	
Exogenous Variable	**1-Month**	**3-Months**	**6-Months**	**3-Months**	**6-Months**
IP [a]	.00917	.0391	.0295	.00633	.00628
CI	.00858	.0399	.0295	.00572	.00516
PE	.00887	.0400	.0299	.00579	.00519
OBP	.00867	.0411	.0301	.00580	.00537
D **CPI**	.00923	.0403	.0301	.00747	.00750
D **CR**	.00910	.0380	.0303	.00646	.00631
D **ES**	.00884	.0407	.0306	.00597	.00608
D **OL**	.00882	.0386	.0284	.00597	.00605
D **SPI**	.00890	.0369	.0275	.00585	.00624
Multivariate [b]	.00988	.0412	.0294	.00622	.00516

[a] Univariate Model : $\Delta IP_t = \alpha_1 + \beta_1 \Delta IP_{t-1} + \beta_2 \Delta IP_{t-2} + \varepsilon_{1,t}$.

[b] Multivariate Model : $\Delta IP_t = \alpha_1 + \sum_{j=1}^{j=2} \beta_i \Delta IP_{t-j} + \sum_{j=1}^{j=7} \gamma_i \Delta CPI_{t-j} + \sum_{j=1}^{j=5} \delta_i \Delta OL_{t-j} +$

$$+\sum_{j=1}^{j=2}\phi_i\,\Delta ES_{t-j}+\sum_{j=1}^{j=4}\varphi_i\,OBP_{t-j}+\sum_{j=1}^{j=7}\theta_i PE_{t-j}+\mathring{a}_{1,t}\,.$$

Table 2 Theil Inequality Coefficients

Table 2.1 France

Exogenous Variable	Set A, Set B 1-Month	Set A 3-Months	Set A 6-Months	Set B 3-Months	Set B 6-Months
IP 1 [a]	.721	.732	.759	.520	.439
IP 2 [a]	.744	.687	.686	.501	.428
CI	.710	.666	.687	.575	.490
PE	.685	.697	.678	.577	.484
OBP	.760	.559	.571	.656	.624
D **CPI**	.685	.649	.640	.532	.369
D **ES**	.745	.543	.623	.543	.423
D **OL**	.810	.642	.657	.657	.570
Multivariate [a]	.713	.537	.631	.547	.395

[a] See notes to Table 1.1.

Table 2.2 Germany

Exogenous Variable	Set A, Set B 1-Month	Set A 3-Months	Set A 6-Months	Set B 3-Months	Set B 6-Months
IP [a]	.776	.828	.789	.719	.701
CI	.724	.769	.686	.650	.642
PE	.695	.767	.696	.689	.639
OBP	.723	.766	.685	.707	.663
D **CK**	.743	.741	.627	.754	.715
D **CPI**	.690	.742	.697	.602	.507
D **ES**	.761	.748	.659	.663	.660
D **OL**	.667	.642	.652	.534	.489
Multivariate [a]	.594	.721	.617	.534	.524

[a] See notes to Table 1.2.

Table 2.3 Italy

	Set A, Set B	Set A		Set B	
Exogenous Variable	**1-Month**	**3-Months**	**6-Months**	**3-Months**	**6-Months**
IP [a]	.638	.812	.853	.641	.599
CI	.552	.824	.812	.526	.491
PE	.523	.821	.821	.516	.517
OBP	.592	.847	.816	.550	.544
D **CPI**	.613	.797	.804	.619	.563
D **CR**	.580	.719	.787	.688	.631
D **ES**	.576	.769	.769	.540	.593
D **OL**	.616	.779	.735	.587	.568
D **SPI**	.644	.706	.708	.586	.578
Multivariate [a]	.576	.694	.637	.538	.461

[a] See notes to Table 1.3.

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