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Cross-checking the Now

...which domestic and external data on industry contain formal leading content for GDP?

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Economic Analysis 46

Abstract

The current study uses two complementary approaches to formally assess the leading content of selected industrial indicators for GDP growth in Slovakia and Germany. In particular, four frequently monitored indicators on industry (new orders, industrial production, manufacturing production, and industrial turnover) are tested for leading properties for their respective economies, using pairwise Granger causality tests and VAR-based impulse response functions. The analysis concludes industrial new orders to be the top performer in Germany, and sales in industry to have the strongest formal leading content in Slovakia. These results are robust across both empirical methods, and the latter finding nicely validates the variable selection in our short-term forecast model MRKVA. Interestingly, German new orders seem to also lead the Slovak economy, albeit to a much less pronounced extent than its domestic economy. These conclusions shed additional light on the quality and properties of high-frequency data we regularly monitor, and in that way improve the efficacy of our forecast monitoring framework.

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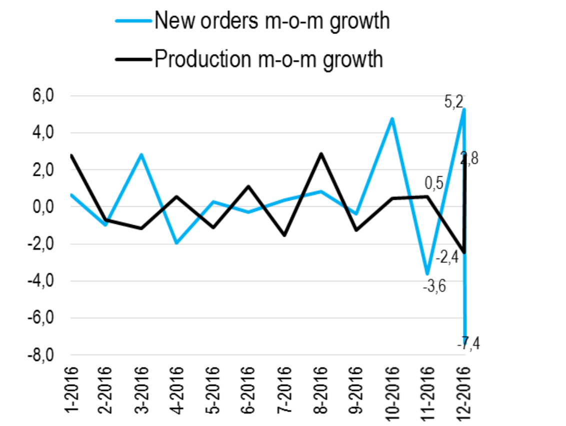
1 Laying Down the Groundwork

1.1 Introduction

Forecasting the direction in which the economy is headed is essential from a viewpoint of macroeconomic policy. Industrial indicators may be valuable insofar as they provide a short-term indication about the direction of the economy. Analysts also frequently monitor industrial indices to cross-check conjunctural developments with survey-based indicators. The Institute for Financial Policy (IFP) closely monitors domestic industrial data as a part of its short-term forecasting routine. In addition, it also tracks monthly industrial developments of its largest trading partners as a part of its external environment monitoring. Domestic and external data on industry, along with their survey-based counterparts, promote informed short-term forecasting.

Often times, however, industrial indicators provide differing signals on a high-frequency basis. For example, in December 2016 industrial production (IP, hereafter) in Germany unexpectedly posted the strongest decline since the Great Recession, while German new orders in manufacturing outperformed market expectations at 5 per cent month on month. The following month, the German IP recovered, while new orders in manufacturing plunged by almost 7 per cent (Chart 1). Such volatile developments in the German industrial sector took place amid distinctly upbeat economic sentiment in Germany (Chart 2) and also within broader euro area.

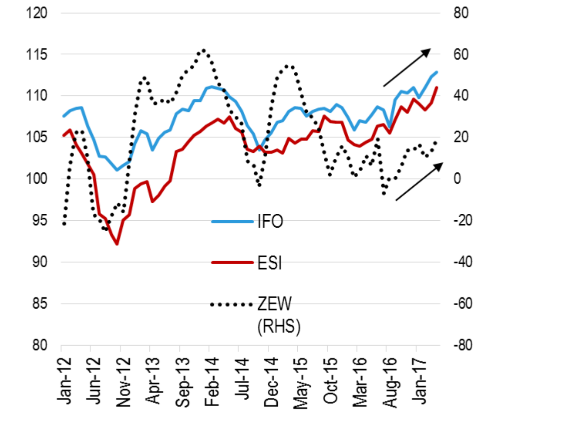
Chart1: Volatile developments in the German industrial sector...



Source: Destatis.

Note: Indices are seasonally and working-day adjusted.

Chart 2: ...amid succeeding months of strong economic sentiment



Sources: IFO, DG,ECFIN, ZEW.

The recent developments in the German industrial sector highlights that not all industrial indices are “created equal” for monitoring real economic activity. Thus, while some may lead real economic activity others may be concurrent, which begs for a formal analysis, which tests actual leading properties of the industrial data we monitor. Moreover, top performers in terms of leading properties may shift in time and vary across countries. The recent experience thus validates a closer scrutiny of a formal character.

Against this backdrop, the current analysis concerns itself with several questions related to industrial indices' formal leading properties for real activity. *One,* how do the German industrial indicators compare to the Slovak ones in terms of formal leading content[1]? *Two,* is the IFP short-term modelling framework MRKVA still timely and relevant in terms of the industrial indices fed into it? *Three,* does any German industrial data lead the Slovak real activity, directly, based on a formal analysis?

All three questions are meaningful from a policy perspective insofar as a more comprehensive and accurate forecasting framework serves as an enhanced basis for macroeconomic policy making. In this case, we focus on the improved efficacy of external environment monitoring, with Germany being Slovakia's largest trading partner. Second, the current analysis also assesses the relevance of Slovak industrial indicators currently fed to our short-term modelling framework. Third, it takes a novel angle by formally studying the leading properties of German industry for the Slovak economy.

1.2 Theory and Literature

Theorizing industrial data as having leading properties for economic activity, requires sizeable industrial sector as a share of country's GDP. In other words, it would not make sense to be trying to examine the link for a country where industry is a negligible part of economic activity. In 2016, the value added of industry as a share of GDP was 34.8 per cent in Slovakia and 30.5 for Germany according to the latest World Bank figures. In terms of the manufacturing sector, the shares were 22.8 per cent for Slovakia and 22.6 per cent for Germany as a share of each country's respective GDP in 2016. Thus, this requirement holds for both examined countries.

Recent studies of industrial indicators as leading series for the Slovak GDP growth postulate the former within a broader framework of composite leading indicators (see for example, Kľúčik 2010). In Germany, the research emphasis is on soft, survey-based predictive ability for its business cycle (for example, Savin and Winker 2012), rather than industry data alone. In terms of empirical method, many studies use dynamic factor model frameworks, MIDAS a VAR approaches to study the interdependencies and evaluate forecasting performance (see for example Kholodilin and Kooths 2008). In terms of individual indicators, industrial new orders have been found to historically anticipate business cycle turning points (de Bondt at el. 2012), while other have found order to lead industrial production (see for Alexander and Stekler 1959). **This analysis' contribution is to zoom onto German and Slovak industrial indicators' predictive properties for their respective business cycles, using formal methods**, without necessarily quantifying how they (fail to) improve forecast performance.

1.3 Empirical Method

Pairwise Granger causality testing makes a good starting point for investigating the potential lead relationship between the short-term industrial statistics and GDP for each country. In the simplest terms, X is said to Granger-cause Y under certain conditions[2], if Y can be better predicted using the histories of both X and Y, than it can be using the history of Y alone. In our

[1] This has been already been studied in the context of IFP's short-term forecasting model MRKVA. For more see: http://www.finance.gov.sk/Default.aspx?CatID=9506

[2] Granger-defined causality relies on two principles: one, the cause happens prior to its effect (or that a cause cannot come after the effect); and, two, that the cause has unique information about the future values of its effect (Granger 1969). Importantly, Granger causality measures precedence and information content but does not by itself indicate causality in the more common use of the term. Also, it should be noted that Granger-causality tests are designed to handle pairs of variables, and may produce misleading results when the true relationship involves more variables.

application, each of the four selected short-term industrial statistics are said to Granger-cause GDP, if current GDP values can be better explained by its own past values and the past values of the short-term industrial statistics, than merely its own past values. Thus, if short-term industrial indicators are found to Granger-predict GDP, the former precedes the latter, as well as contains unique information about the future values of the latter.

However, Granger-causality may not tell us the complete story about the interactions between the variables of a system. In an applied work, it is often of interest to know the response of one variable to an impulse in another variable. If there is a reaction of one variable to an impulse in another variable, we may call the latter causal for the former.

The second empirical method deployed, therefore, is an impulse response analysis based on an unrestricted bivariate vector autoregressive model. Each model consists of one of the four short-term industrial indicators and GDP. An impulse response function (IRF) traces the effect of a one-time shock to one of the innovations on current and future values of the endogenous variables. In our case, the IRFs plot the adjustment of GDP to an unexpected temporary shock in one of the four short-term industrial indicators. If GDP reacts to a shock in one of the four short-term industrial indicators, this indicator is causal for GDP. **Thus, while pairwise Granger causality tests test for the average impact of one variable on another, IRF focus in the bivariate relationship when an unexpected shock occurs.**

BOX 1: The Data

The data on German and Slovak GDP are sourced on a quarterly basis from the ECB's Statistical Data Warehouse as chain-linked volumes at constant prices in euro over the period Q1-1995 to Q4-2016. The set of monthly industrial indicators deployed in the estimations are summarized in Table 1. **They were selected because they constitute notoriously monitored data on industry by markets and analysts alike, yet they capture reasonable diverse economic concepts (see Table 2).** All indicators come from their respective national statistical offices. The German monthly series are seasonally and working day adjusted by the German statistical office, DESTATIS, using the ARIMA-12 method. The Slovak IP index starts only in 2000, while new orders are available from 2009[3]. The index base for all monthly series is 2010=100. All high-frequency hard data are averaged over quarter to attain the same quarterly frequency as national accounts for empirical purposes.

Table 1. Monthly Industrial Data Overview

Country	Manufacturing index	Source	Time Coverage
Slovakia	New orders in manufacturing	Slovak Statistical Office	Jan-2009 to Jan-2017
Slovakia	Industrial turnover	Slovak Statistical Office	Jan-1995 to Jan-2017
Slovakia	Industrial production	Slovak Statistical Office	Jan-2000 to Jan-2017
Slovakia	Industrial production (manufacturing)	Slovak Statistical Office	Jan-2000 to Jan-2017
Germany	New orders in manufacturing	Destatis	Jan-1995 to Jan-2017
Germany	Industrial turnover	Destatis	Jan-1995 to Jan-2017
Germany	Industrial production	Destatis	Jan-1995 to Jan-2017
Germany	Industrial production (manufacturing)	Destatis	Jan-1995 to Jan-2017

Source: National Statistical Offices.

[3] Longer historical series on new orders have been requested from the Slovak statistical office, but the request was rejected on the basis that these series prior to 2009 "did not meet the desired quality and were put on a list of negative priorities by the European statistical office, Eurostat".

New orders in manufacturing capture the value of all legally binding contracts between a producer and a consumer for future deliveries. In contrast, industrial turnover measures the totals invoiced by the seller during the reference period, corresponding to market sales of goods or services supplied to third parties. IP measures the overall volume of output generated by all industrial sector, while manufacturing production measures merely manufacturing output, without mining and public utilities.

Table 2. Economic Concepts Captured by High-frequency Indices on Industry

Manufacturing index	Economic Concept it Captures	Timeliness of publication
New orders in manufacturing	The value of orders received by the unit during the reference period	45 days after the end of the reference period
Industrial turnover	Sales in industry (including rebates and price deductions, does not include VAT)	45 days after the end of the reference period
Industrial production	The volume of output generated by industrial sectors such as manufacturing, energy and public utilities	45 days after the end of the reference period
Industrial production (manufacturing)	The volume of output generated by the manufacturing sector (excl. mining and energy)	45 days after the end of the reference period

Sources: Eurostat and OECD.

2 Empirical Findings

2.1 Pairwise Granger Causality Tests

German new orders in manufacturing exhibit the strongest leading performance for German GDP, based on pairwise Granger causality tests (Table 3). In fact, new orders with lag order 1 (bold red) are the top performer with F-stat score almost four-fold of the second best performer (new orders lag order 4). To interpret the F-test more specifically, one quarter lagged values of new orders in manufacturing jointly improve GDP forecast fourfold, compared to four quarters lagged new orders. At the same time, Granger causality runs unidirectionally – from new orders to GDP – but not the other way around (grey italics).

Table 3: Pairwise Granger causality tests with industrial indices and GDP for Germany[4]

Germany		F-stat	prob	# obs	lags
	growth rates of variables				
1	**GNEWORDERS_DE does not Granger Cause GGDP_DE**	**38,1**	**0,0**	**86**	**1**
	GGDP_DE does not Granger Cause GNEWORDERS_DE	*1,2*	*0,3*	*86*	*1*
		11,7	0,0	83	4
		0,3	*0,9*	*83*	*4*
2	GTURNOVER_DE does not Granger Cause GGDP_DE	3,0	0,1	86	1
	GGDP_DE does not Granger Cause GTURNOVER_DE	*1,8*	*0,2*	*86*	*1*
3	GIP_DE does not Granger Cause GGDP_DE	7,3	0,0	86	1
	GGDP_DE does not Granger Cause GIP_DE	*0,0*	*1,0*	*86*	*1*
4	GIPMNFG_DE does not Granger Cause GGDP_DE	11,6	0,0	86	1
	GGDP_DE does not Granger Cause GIPMNFG_DE	*0,3*	*0,6*	*86*	*1*

Source: IFP estimates.

[4] In all cases, the pairwise Granger test tests whether we find sufficient statistical evidence to reject the hypothesis that a variable on industry does not Granger-cause GDP. F-stat stands for the F-statistics, "prob" stands for probability, "# obs" stands for the number of observations in the estimation, and "lags" corresponds with the lag length, chosen based on optimal lag length criteria. For each of the 4 pairs of tests, black/red represents an industrial indicator and GDP, while gray italics represents the same pair with a reversed causality tested (GDP and an industrial indicator). This applies for all tables in section 2.1.

Notes:"GGDP_DE" stands for real GDP growth in Germany. "GNEWORDERS_DE" and "GTURNOVER_DE" stand for growth in German new orders and industrial turnover, while "GIP_DE" and "GIPMNFG_DE" stand for growth in German industrial production and manufacturing production, respectively.

Simple OLS estimations consisting of the variable pairs as reported in Table 3, with ideal lag orders as reported in the last right-hand-side column, yield the same ranking in terms of explanatory power. One-period lagged new order growth explains about 37 per cent of variability in German GDP, followed by one period lagged manufacturing production growth (20 per cent), one period lagged industrial production growth (17 per cent), and one period lagged turnover growth (13 per cent).

Interestingly, the Granger causality tests suggest that the production variables, too, contain some unique information about the future values of GDP. While production is conventionally viewed as a concurrent indicator, it is not completely implausible that it has some valuable leading content, given that e.g. NBER uses IP to anticipate peaks and troughs in the business cycle. Notably, IP data are volatile and heavily revised and hence a more detailed, real-time analysis would be required to disentangle the strength and the order of this relationship. For the purpose of the current analysis, these results are cross-checked with the second empirical method for robustness.

Turning to the pairwise Granger causality tests for Slovakia, the Slovak industrial turnover growth lagged by one quarter Granger predicts the Slovak GDP growth with most statistical significance (Table 4). In line with the theory, this relationship is unidirectional. Furthermore, similar to the German case, headline IP also seems to contain unique information for the future values of GDP growth. At the same time, contrary to the German case, there is no statistical evidence that new orders lead the Slovak GDP growth.

Table 4: Pairwise Granger causality tests with industrial indices and GDP for Slovakia

Slovakia						
	growth rates of variables	F-stat	prob	# obs	lags
1	GNEWORDERS_SK does not Granger Cause GGDP_SK	0,0	0,9	30	1
	GGDP_SK does not Granger Cause GNEWORDERS_SK	*0,5*	*0,5*	*30*	*1*
		1,1	0,4	29	2
		0,8	*0,4*	*29*	*2*
2	**GTURNOVER_SK does not Granger Cause GGDP_SK**	**9,1**	**0,0**	**86**	**1**
	GGDP_SK does not Granger Cause GTURNOVER_SK	*0,0*	*0,9*	*86*	*1*
3	GIP_SK does not Granger Cause GGDP_SK	8,5	0,0	66	1
	GGDP_SK does not Granger Cause GIP_SK	*3,9*	*0,1*	*66*	*1*
4	GIPMNFG_SK does not Granger Cause GGDP_SK	2,5	0,1	66	1
	GGDP_SK does not Granger Cause GIPMNFG_SK	*12,6*	*0,0*	*66*	*1*

Source: IFP estimates.

Notes: "GGDP_SK" stands for real GDP growth in Slovakia. "GNEWORDERS_SK" and "GTURNOVER_SK" stand for growth in Slovak new orders and industrial turnover, while "GIP_SK" and "GIPMNFG_SK" stand for growth in Slovak industrial production and manufacturing production, respectively.

OLS estimations consisting of the variable pairs as reported in Table 4, with ideal lag orders as reported in the last right-hand-side column, yield turnover and industrial production having stronger explanatory power for Slovak GDP growth (albeit ranging only from 6-10 per cent) than manufacturing production or new orders (below 5 per cent, with new orders being the under-dog).

Turning to the pairwise Granger causality tests amongst German industrial data and Slovak GDP, German new orders in manufacturing as well as manufacturing production both Granger predict Slovak GDP (Table 5). The two indicators have performed almost equally well (top performer in bold red, second best in bold black). Correspondingly, OLS estimation results consisting of the variable pairs as reported in Table 5, with ideal lag orders as reported in the last right-hand-side column, show German new orders and both production variables to explain 8-9 per cent of variability in Slovak GDP, while German turnover in industry does not seem to be helpful in that respect.

Table 5: Pairwise Granger causality tests with for German industrial indicators and Slovak GDP

German manufacturing indicators and Slovak GDP					
	growth rates of variables	F-stat	prob	# obs	lags
1	**GNEWORDERS_DE does not Granger Cause GGDP_SK**	**13,1**	**0,0**	**86**	**1**
	GGDP_SK does not Granger Cause GNEWORDERS_DE	*7,3*	*0,0*	*86*	*1*
	GNEWORDERS_DE does not Granger Cause GGDP_SK	4,1	0,0	83	4
	GGDP_SK does not Granger Cause GNEWORDERS_DE	*2,7*	*0,0*	*83*	*4*
2	GTURNOVER_DE does not Granger Cause GGDP_SK	6,7	0,0	86	1
	GGDP_SK does not Granger Cause GTURNOVER_DE	*0,8*	*0,4*	*86*	*1*
3	GIP_DE does not Granger Cause GGDP_SK	12,7	0,0	86	1
	GGDP_SK does not Granger Cause GIP_DE	*0,5*	*0,5*	*86*	*1*
4	**GIPMNFG_DE does not Granger Cause GGDP_SK**	**13,6**	**0,0**	**86**	**1**
	GGDP_SK does not Granger Cause GIPMNFG_DE	*1,5*	*0,2*	*86*	*1*

Source: IFP estimates.

The bidirectional[5] relationship of German new orders and Slovak GDP could be connected to the close import-export ties of the two economies in the automotive industry and their close integration in global value chains, but such hypothesis requires further scrutiny[6]. To the contrary, Slovak new orders contained leading properties *neither* for Slovak GDP, *nor* for Slovak IP[7], yielding them worthless from a viewpoint of short-term forecasting.

Nevertheless, Granger-causality focuses on the average impact, and may not tell us the whole story about the interactions of variables in a system. Another way to investigate whether one variable leads another, is by the virtue of a response to an exogenous shock ("innovation"). If there is a reaction of one variable to an impulse in another variable, we may call the latter causal for the former. Hence, we turn to the bivariate VAR-based impulse response functions to see whether the GDP variables actually react to one innovation shocks in industrial indicators.

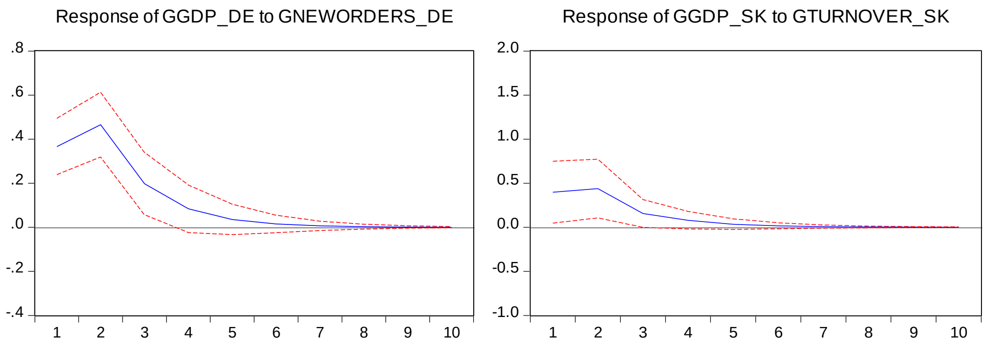
2.2 VAR-based Impulse Response Functions (IRFs)

Impulse response functions (IRF) based on an unrestricted bivariate vector autoregressive models consist of each of the four short-term manufacturing indicators and GDP. An unexpected temporary shock in new orders leads to a change of +0.5 per cent in GDP growth at its peak after two quarters. Chart 5 (left-hand-side) shows that one standard deviation exogenous shock in German new order growth is followed by a significant delayed adjustment of German GDP growth. At the same time, German new orders do not react to a shock in GDP at all[8]. No such delayed adjustment in GDP was observed for any of the remaining three indicators in Germany[9]. Moreover, this result is consistent with that yielded by Granger-causality tests in terms of top performer.

[5] The Slovak GDP lag 1 also precedes German new orders in manufacturing. The reversed Granger test is only half as strong as the original one.
[6] Running quick checks for Granger causality between German and Slovak new orders with lag 1, some evidence was found that German new orders unilaterally precede Slovak new orders. This is in line with the import-export hypothesis.
[7] The Granger causality tests between Slovak new orders and Slovak IP were conducted based on a theoretical rationale. It is established in the literature that new orders lead production. The results are available upon request.
[8] The opposite direction IRF results are not shown; but are available upon request.
[9] These results are not included in the analysis, but are available upon request.

Chart 5. Bivariate impulse response function of German GDP to German industrial new orders (LHS) and Slovak GDP to Slovak industrial turnover (RHS)[10]

Response to Cholesky One S.D. Innovations ± 2 S.E. Response to Cholesky One S.D. Innovations ± 2 S.E.



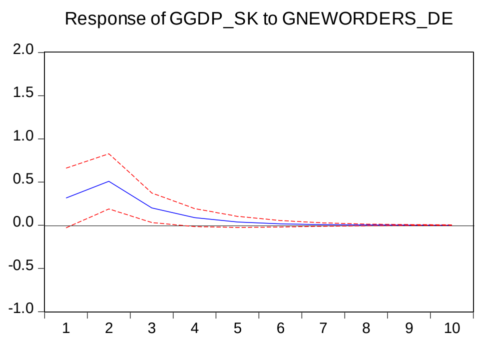
Source: IFP estimates.

In case of Slovakia (right-hand-side Chart 5), IRFs confirm the top performer to be industrial turnover. In fact, like in the German case, the other manufacturing variables do not trigger an equivalent reaction in GDP. The chart shows that one innovation shock in industrial sales triggers close beneath 0.5 per cent change in GDP in the Slovak case at its peak after two quarters. At the same time, the reaction runs in one direction only – from the statistically significant indicators to GDP – but not the other way around[11].

Interestingly, Slovak GDP reacts also to an exogenous temporary shocks in German new orders. One innovation shock in the industrial variable triggers about 0.5 per cent change in GDP, peaking at two quarters (Chart 6).

Chart 6. Bivariate impulse response function of Slovak GDP to German industrial new orders

Response to Cholesky One S.D. Innovations ± 2 S.E.



Source: IFP estimates.

BOX 2: The Model Diagnostics

Both empirical methods require the times series used to follow a stationary process in order to produce meaningful results. A standard Augmented Dickey-Fuller (ADF) stationarity test is performed on logarithmically transformed levels of all series, as well as their changes, and growth rates. Table 7 provides an overview of the diagnostics. In particular, it reveals the

[10] X-axis contains number of quarters. The impulse responses are based on non-factorized one unit innovations (temporary exogenous shocks). This holds for all charts in section 2.2.
[11] The opposite direction IRF results are not included; but are available upon request.

presence of a unit root for levels (in red), but no longer for log levels or growth rates (in blue). **Growth rates of all variables are used in the estimations for their ease in interpretation.**

Table 7. ADF diagnostics

Augmented Dickey Fuller Test (ADF)

Null Hypothesis (ADF): Variable has a unit root.

		Germany				Slovakia			
	Variable	# obs	lag length	test stat	prob	# obs	lag length	test stat	prob
LOG LEVELS	LGDP	86	1	-0,7	0,8	87	0	-1,1	0,7
	LNEWORDERS	84	4	-1,7	0,4	31	0	-7,9	0,0
	LTURNOVER	87	1	-1,3	0,6	86	1	-1,2	0,7
	LIP	87	1	-1,5	0,5	66	1	-1,0	0,7
	LIPMNFG	87	1	-1,5	0,5	67	0	-0,8	0,8
LOG CHANGES	LDGDP	86	0	-6,5	0,0	86	0	-9,8	0,0
	LDNEWORDERS	84	3	-5,3	0,0	26	4	-5,0	0,0
	LDTURNOVER	87	0	-6,1	0,0	86	0	-5,5	0,0
	LDIP	87	0	-5,8	0,0	66	0	-6,0	0,0
	LDIPMNFG	87	0	-5,5	0,0	66	0	-7,1	0,0
GROWTH RATES	GGDP	86	0	-6,5	0,0	86	0	-9,9	0,0
	GNEWORDERS	84	3	-5,3	0,0	26	4	-5,3	0,0
	GTURNOVER	87	0	-6,0	0,0	86	0	-5,6	0,0
	GIP	87	0	-5,8	0,0	66	0	-6,1	0,0
	GIPMNFG	87	0	-5,5	0,0	66	0	-7,2	0,0

Source: IFP estimates.

Furthermore, standard lag length selection information criteria are deployed to pin down the optimal model on which Granger causality/IRF would be performed. A conventional way to select the lag order for Granger causality tests is to fit a univariate VAR model and track the information criteria for each lag length. The optimal lag length for most variables is one quarter, with some exceptions as reported in Table 8.

Table 8. Optimal lag selection – Granger-causality tests[12]

	Germany					Slovakia				
univariate VAR lag length diagnostics	**AIC**	**SC**	**HQ**	**# obs**	**lag length**	**AIC**	**SC**	**HQ**	**# obs**	**lag length**
GGDP	0,6	2,3	2,4	77	**1**	4,0	4,1	4,0	77	**0**
GNEWORDERS	5,2	5,4	5,3	78	**4**	4,4	4,6	4,5	29	**2**
GTURNOVER	4,7	4,7	4,7	78	**1**	5,4	5,5	5,4	77	**1**
GIP	4,1	4,1	4,1	78	**1**	5,6	5,6	5,6	57	**1**
GIPMNFG	4,1	4,2	4,1	78	**1**	6,2	6,2	6,2	57	**0**

Source: IFP estimates.

Same information criteria are used for VAR model selection (Table 9). The VAR equations are re-estimated with the ideal lag order suggested by the information criteria reported in Table 9, and only then the IRF analysis is conducted.

[12] Theoretically, an optimal lag order can be different for two variables and the Granger test would be still appropriate. It is the practical implementation of the Granger test, however, which constrains us to the same number of lags for a pair of variables. Therefore, where a lag order different than one is suggested by the information criteria, additional pairwise Granger causality tests would be run with the suggested lag order. For example in a pairwise Granger test for new orders and GDP in Germany, the test would be conducted for lag order one and four.

Table 8. Optimal lag selection – Granger-causality tests

			Germany		
bivariate VAR regressions with GDP	**AIC**	**SC**	**HQ**	**# obs**	**lag length**
GNEWORDERS	6,9	7,1	7,0	77	**1**
GTURNOVER	5,9	6,1	6,0	77	**1**
GIP	5,3	5,4	5,3	77	**1**
GIPMNFG	5,4	5,6	5,5	77	**1**
			Slovakia		
bivariate VAR regressions with GDP	**AIC**	**SC**	**HQ**	**# obs**	**lag length**
GNEWORDERS	4,3	4,7	4,4	27	**2**
GTURNOVER	9,3	9,5	9,4	77	**1**
GIP	9,0	9,6	9,2	57	**4**
GIPMNFG	9,7	10,3	10,0	57	**4**
	German short-term manufacturing data and Slovak GDP				
bivariate VAR regressions with Slovak GDP	**AIC**	**SC**	**HQ**	**# obs**	**lag length**
GNEWORDERS	9,2	9,3	9,2	77	**1**
GTURNOVER	8,5	8,7	8,6	77	**1**
GIP	7,9	8,1	8,0	77	**1**
GIPMNFG	7,9	8,1	8,0	77	**1**

Source: IFP estimates.

3 Conclusions and Outlook

This policy note formally tests leading properties of selected German and Slovak industrial indicators for GDP. It finds that, ***first,* in Germany, we should look for clues in industrial new orders above all** for new orders exhibit the best formal leading performance for its real activity. This finding is robust across two different methods. The performance of new orders also is particularly pronounced *on average*, using the Granger causality approach.

***Second*, this analysis yields sales in industry as the most probable industrial leading indicator for Slovak GDP**. This finding is broadly consistent with IFP's selection of sales of tradeables[13] over other monthly hard data on the real economy in its short-term modelling framework MRKVA. The second finding of this analysis thus further validates the choice of hard monthly indicator on industry in our formal short-term forecasting framework.

***Third*, several German manufacturing indices also seem to contain formal leading content for the Slovak GDP**. This finding is likely linked to both economies' close integration in global value chains, in particular in the automotive industry, but further research would be required to validate this. Future work may also involve re-running the exercise with updated (in terms longevity and quality) new order series for Slovakia. In addition, it would be interesting to compare the current analysis' results with those obtained from real-time vintages of all series. Further work may also include looking into survey-based indicators. This could yield more comprehensive leading performance rankings, generating even more gains for our short-term GDP forecasting framework.

[13] Sales of tradeables includes industry and construction, while industrial turnover only includes sales in industry.

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