The Kiel Institute for the World Economy
Düsternbrooker Weg 120,
D-24105 Kiel

Working Paper No. 436

Predicting GDP Components.

Do Leading Indicators Increase Predictability?

by

Jonas Dovern

July 2006

PREDICTING GDP COMPONENTS

DO LEADING INDICATORS INCREASE PREDICTABILITY?

JONAS DOVERN

July 10, 2006

Abstract. We use the concept of predictability as presented in Diebold and Kilian (2001) to assess how well the growth rates of various components of German GDP can be forecasted. In particular, it is analyzed how well different commonly used leading indicators can increase predictability of these time series. To this end, we propose an algorithm to select an "optimal" information set from a full set of possible leading indicators.

In the univariate set up, we find very small degrees of predictability for all quarterly growth rates whereas yearly growth rates seem to be more predictable at short forecast horizons. According to the algorithm proposed, from a set of financial leading indicators the short term interest rate is included in the highest number of information sets and from a set of survey indicators the ifo-business expectation index is included in most cases. Conditioning on the "optimal" sets of leading indicators improves the predictability of most of the quarterly growth rates substantially while the predictabilities of the yearly growth rates cannot be increased significantly further.

The results indicate that there is clearly evidence that "complicated" forecasting models are usually superior to simple AR univariate models.

Keywords: Predictability, Leading Indicators, GDP components

JEL Classification: C53, E37

Jonas Dovern, Kiel Institute for the World Economy (IfW), `jonas.dovern@ifw-kiel.de`. I thank Carsten-Patrick Meier for many helpful comments.

1. Introduction

It is a well known fact that some time series are notoriously hard to forecast while relatively good short-term forecasts can be made for other time series. In this paper, we want to assess the predictability of the disaggregated components of German GDP by using the concept of predictability that is presented in Diebold and Kilian (2001). The focus lies on the analysis of leading indicator's ability to improve the predictability of the GDP components.

Forecasters of macroeconomic time series have to deal with the problem that the true contemporaneous state of the economy is usually unobservable for them for some period. The reasons are, first, the lagged publication of official statistics and, second, subsequent data revisions. The high uncertainty about the current values of macroeconomic time series makes it much harder to produce accurate predictions of future realizations than if the state of the economy would be known at the time of the forecast. Leading indicators, which forego the actual business cycle activity with some lead, are widely used instruments to deal with this problem. The indicators considered in this paper can broadly be classified into two groups: financial variables – such as the development of stock market indices or interest rates – on the one hand and survey indicators – such as the business expectation index published by the ifo institute – on the other hand. Both groups share the feature that the data are available very frequently (even virtually continuously in case of financial data) and without any huge time lag (even instantaneously for financial data).

It is generally accepted that conditioning forecasts for macroeconomic variables on leading indicators helps to reduce prediction errors considerably in most cases. However, comprehensive formal inspections of this issue, which include an assessment of the indicators' ability to improve on the prediction of growth rates of various GDP components, are rarely to be found in the literature. Most studies concentrate only on forecasts of aggregated GDP growth and inflation. These contributions include among others Fritsche and Stephan (2000), Kholodilin and Siliverstovs (2005) and the references therein for Germany, Cecchetti et al. (2000), Banerjee and Marcellino (2006) for the US, and Banerjee et al. (2003) for the Euro area.

Whereas most of these papers judge the benefits resulting from leading indicators by focusing on the latter's ability to reduce the RMSE of out-of-sample forecasts, we rely on the concept of predictability as introduced in the most general framework by Diebold and Kilian (2001). Predictability – in essence – is measured by the relative loss of a short-term forecast for a time series compared to the loss of a long-term forecast. Clearly, it is a population property and has to be estimated from the one realized sample path of a time series. To this end, we will follow the approach of Diebold and Kilian that involves fitting a parametric uni- or multivariate model to the data in a first step. In the second step, the population parameters are replaced by its estimates for the computation of the predictability measure.

Although the concept has not been used extensively in the literature yet, it is suitable for a wide range of applications. It has been used for instance in the following contributions. Barsky (1987) assesses the degree of predictability of quarterly and yearly US inflation rates. Galbraith and Kisinbay (2005) analyze the predictability of daily variances of returns for various financial time series in GARCH and FIGARCH frameworks. Anderesen et al. (2004) use the degree of predictability as one measure to characterize the nature of *betas* of single financial assets' returns with regard to the market return. Brisson et al. (2001) employ the concept in the context of using diffusion index forecasting models to predict growth rates of real GDP and investment. Diebold and Kilian (2001) propose to use the predictability of time series as one characteristic feature that might be used to assess the validity of macroeconomic models. They compare the estimated predictabilities of real data and simulation outcomes of a labor model (originally by Hansen, 1985) to judge whether the model is able to produce time series that have the same character than the real data.

The remainder of the paper is structured as follows. In section 2 we expose the theoretical foundations for the predictability measure. In section 3 we briefly report what data we use for the empirical analysis. In section 4 we analyze the predictability of different GDP components for Germany and the ability of various leading indicators to improve on those predictablities. Finally, we conclude the paper in section 5.

2. Predictability

It is clear that even for good forecasts of time series the forecasted and actual values will differ. Some time series can, however, be forecasted better than others. The predictability of a time series is a measure of how well the series can be forecasted. A bunch of different measures for predictability can be found in the literature. Early concepts (Jewell and Bloomfield, 1983, Hannan and Poskitt, 1988, or Granger and Newbold, 1986) usually compare the expected loss of a short-term forecast to the unconditional variance of a time series.

Granger and Newbold for instance propose as a measure of predictability for covariance stationary time series:

$$P_{GN}(j) = 1 - \frac{var(e_{t+j,t})}{var(y_{t+j})}, \tag{1}$$

where $e_{t+j,t} = y_{t+j} - \hat{y}_{t+j,t}$ denotes the forecast error of the optimal forecast $\hat{y}_{t+j,t}$. This measure is, however only applicable for covariance stationary time series and allows only for univariate information set and quadratic loss functions.

Diebold and Kilian (2001) generalize the concept to allow (i) the assessment of non-stationary time series, (ii) multivariate information sets, (iii) a wide range of different loss functions, and (iv) the possibility to tailor the measure to different forecast situations.[1] More formal, they propose to base a natural measure of predictability on the difference between the conditionally expected loss of an optimal short-run forecast, $E[L(e_{t+j,t})|\Omega]$, and that of an optimal long-run forecast, $E[L(e_{t+k,t})|\Omega]$, $j \ll k$, where $E[\cdot]$ denotes the mathematical expectation operator and Ω is the information set, on which the forecasts are conditioned. The measure for predictability is defined analogously to P_{GN}:[2]

$$P_{DK}(L, \Omega, j, k) = 1 - \frac{E[L(e_{t+j,t})|\Omega]}{E[L(e_{t+k,t})|\Omega]} \tag{2}$$

It is clear that predictability is a property of the population rather than of the realized sample path. We can, however, estimate the predictability from one observed sample path. To this end we first estimate a parametric model and use the parameter estimates to construct $P_{DK}(\cdot)$. Obviously, the measure of predictability will depend on the

[1] A good overview and an application of the concept by Diebold and Kilian can also be found in Galbraith (2003).

[2] Note that P_{GN} emerges from P_{DK} if the series is covariance stationary, $L(e) = e^2$, Ω is an univariate information set, and $k = \infty$.

choice of the model. In this paper we focus on the use of vector autoregressive (VAR) models. Given that we face a VAR(q) process[3]

$$y_t = D_t + A_1 y_{t-1} + \ldots + A_q y_{t-q} + \varepsilon_t, \tag{3}$$

with y_t being a vector of time series, D_t is a matrix of deterministic regressors, A_i are coefficient matrices, and ε_t is a vector of independent innovations having a covariance matrix Σ_ε. To keep things simple we will henceforth work with a quadratic loss function. Under this assumption the conditional expectation will be the optimal h-step-ahead forecast, i.e. the forecast with minimum MSE. An analytical form for the h-step-ahead forecast MSE matrix is given by

$$\Sigma_y(h) = \sum_{i=0}^{h-1} \Phi_i \Sigma_\varepsilon \Phi_i', \tag{4}$$

where $\Phi_0 = I_n$ and $\Phi_i = \sum_{j=1}^{i} \Phi_{i-j} A_j$ for $i = 1, 2, \ldots$. Obviously, P_{DK} is then given by $1 - \frac{\Sigma_y^n(j)}{\Sigma_y^n(k)}$, where $\Sigma_y^n(h)$ denotes the n^{th} diagonal element of $\Sigma_y(h)$ with n being the position of the variable of interest in the VAR ordering. We estimate P_{DK} simply by replacing all elements of the A_i by their estimates and selecting the proper diagonal elements of $\Sigma_y(h)$.[4]

Generally, $P_{DK}(L, \Omega, j, k)$ will be a function monotonically decreasing in j, with $\lim_{j \to k} P_{DK}(L, \Omega, j, k) = 0$. As summary statistics, which help to formally assess and compare predictabilities of different time series or for one time series conditioned on different information sets, we propose the following three statistics: namely what we will call

[3]In practice, we determine the optimal lag length for each specification on basis of the Akaike Information Criterion (AIC) since the AIC is less likey to underestimate the lag order compared to other information criterions and,therefore, guarantees to preserves the higher-order dynamis in P_{DK} (Kilian, 2001).

[4]Confidence intervals for $\hat{P}_{DK}$ (for stationary times series) can be constructed by bootstrap methods as proposed in Diebold and Kilian (2001). In addition, the lag order can be treated as endogenous in each bootstrap replication as proposed in Kilian (1998).

One-Step Predictability, *Halflife (of Predictability)*, and *Accumulated Predictability.*

The *One-Step Predictability* of a time series is simply defined by

$$P^0_{DK} = P_{DK}(L, \Omega, 1, k).$$

The *Halflife* of a time series' predictability is defined as

$$HL_{P_{DK}} = \left\{ \arg\min_h |P_{DK}(L, \Omega, h, k) \leq \frac{1}{2} P^0_{DK} \right\}.$$

The *Accumulated Predictability* of a time series is given by

$$\Sigma_{P_{DK}} = \sum_{j=1}^{\bar{j}} \theta^{j-1} P_{DK}(L, \Omega, j, k),$$

where $\bar{j}$ is a truncation point for the sequence of weighted predictabilities (usually set equal to the maximal forecast horizon of interest) and $\theta \in [0; 1]$ is the parameter that determines the shape of the series of geometrically declining weights.[5] Note that for $\theta = 1$ the predictabilities for all forecast horizons up to $\bar{j}$ are given the same weight whereas for $\theta = 0$ only P^0_{DK} is relevant. For the remainder of the paper we set $\theta = 0.5$.

3. Data

We use quarterly data from the German national accounts from 1973Q1 to 2004Q4 for private consumption, government consumption,

[5]In general, θ could be allowed to be larger than one. It is, however, not clear to the author in which circumstances one would give relatively more weight to predictablities of larger forecast horizons.

fixed investment (in plant and equipment), building investment, exports, imports, and aggregated GDP.[6] All time series are converted to real figures by using the adequate price deflator.

The literature about leading indicators and their benefits for forecasting economic time series is full of proposals for good leading indicators. And the number of potential leading indicators is indeed virtually unlimited.[7] We do, however, limit the total set of potential leading indicators, which are considered for an inclusion in the multivariate information sets in the next section, to the following most important indicators: The ifo-assessment of business situation index (*ifogl*), the ifo-business expectation index (*ifoge*), the GfK-consumer confidence index (CC), and the US purchasing manager index (PMI) published by the Institute for Supply Management as well as the short-term (i^{short}) and long term real interest rates (i^{long}), the change in deposits (ΔDep), the return of the German stock market measured by the percentage change of the DAX (ΔDax), and the money stock growth ($\Delta M3$).

In Table 1 the results of a simple correlations analysis between all GDP components and the leading indicators are presented. The numbers in the table indicate the lag of the leading indicator, for which the correlation between the (growth rate of the) GDP component and the leading indicator is maximized.[8] We check lag orders from 5 to -5 (a lead of 5 quarters). Although the picture is not clear cut, the leading

[6]We rely on data for West-Germany for the period prior to 1991Q1. We use growth rates to concatenate the series in 1991Q1. Our data set starts in 1973Q1 as the consumer confidence index (see below) is only available from this quarter on. The sample end point 2004Q4 is chosen since the accounting standards did change substantially in 2005. We want to avoid any influence of this structural break on our results.

[7]For a very complete list of potential leading indicators see Kholodilin and Siliverstovs (2005), table 2.

[8]Due to spacial reasons we do not present the actual correlation coefficients here. They are, however, all positive and of reasonable size. They are available from the author upon request.

TABLE 1. Correlations between GDP components and Leading Indicators

Q-to-Q changes on quarterly frequency									
	ifoge	*ifogl*	*CC*	*PMI*	ΔDep	i^{short}	i^{long}	$\Delta M3$	ΔDax
GDP	0	-1	0	1	3	-1	0	1	3
Pr.Consumption	1	-3	0	-3	0	-4	-2	-2	-1
Gvnt.Consumption	5	3	3	4	-4	3	-2	-5	-4
Fixed Inv.	0	-3	-2	-1	2	-1	-2	5	0
Building Inv.	-1	-3	-2	-3	4	-4	0	0	3
Exports	0	-1	4	1	4	-1	0	4	3
Imports	1	-2	-1	0	5	-2	0	5	3
Y-to-Y changes on quarterly frequency									
	ifoge	*ifogl*	*CC*	*PMI*	ΔDep	i^{short}	i^{long}	$\Delta M3$	ΔDax
GDP	2	-1	0	1	5	-2	4	3	3
Pr.Consumption	2	-1	0	-1	3	-3	-4	0	5
Gvnt.Consumption	5	4	5	5	5	4	4	-2	-5
Fixed Inv.	1	-1	0	1	5	-2	-2	5	3
Building Inv.	2	-1	-1	0	3	-2	-1	1	3
Exports	2	0	-1	3	5	0	0	5	3
Imports	1	-1	-1	2	5	-2	0	4	3

indicators are indeed leading the GDP components, i.e. the correlation is maximized for a lag of the leading indicator, in the majority of combinations. From this very simple analysis the most promising indicators seem to be *ifoge*, *PMI*, ΔDep, $\Delta M3$, and ΔDax. On the other hand, *ifogl* and the two interest rates seem to have almost no predictive power.

4. Empirical Analysis

To analyze the data described in the last section, we use the theoretical framework of section 2. We examine estimates of the various degrees of predictability based on univariate, full multivariate information sets as well as based on what we will call "optimal" information sets.

4.1. **Univariate Information Sets.** To gain an initial insight into the different characteristic features regarding the predictability of the different GDP components, we first present estimates of predictabilities based on univariate information sets, i.e. estimated from simple

Table 2. Results for predictability based on univariate information sets: Q-to-Q changes

	Model	P^0_{DK}	$HL_{P_{DK}}$	$\Sigma_{P_{DK}}$
GDP	AR(1)	0.000780	2	0.000780
Pr.Consumption	AR(5)	0.180119	3	0.262980
Gvnt.Consumption	AR(1)	0.098987	2	0.104140
Fixed Inv.	AR(1)	0.016982	2	0.017130
Building Inv.	AR(4)	0.223393	2	0.305560
Exports	AR(1)	0.000174	2	0.000170
Imports	AR(1)	0.002148	2	0.002150

autoregressive models. We estimate the optimal lag length on basis of the AIC as proposed in Kilian (2001) to preserve the higher order dynamics in P_{DK} by avoiding any underestimation of the lag length that might arise from the use of the BIC.[9] We chose to set $\bar{j} = 12$ and $k = 40$ when analyzing quarterly growth rates and $\bar{j} = 7$ and $k = 12$ when analyzing yearly growth rates. Inference is, throughout this analysis, based on standard non-parametric bootstrap simulations (Runkle, 1987, Horowitz, 2001) with 500 replications, in which we treat the lag order as uncertain and estimate it repeatedly during each simulation run as exemplified in Kilian (1998). The results for the prediction of quarter-to-quarter growth rates are given in Table 2 and visualized in Figure A.1 of the appendix. Only two components show some degree of non-zero predictability: private consumption and building investment. Also for these time series, however, the initial predictabilities of .15 and .20 respectively are remarkably low. All series have in common that $HL_{P_{DK}}$ is quite low. After two quarter (three for private consumption) the predictability is already less than half of the *One-Step Predictability*, i.e. for a forecast horizon of three quarters (four quarters for private consumption). In sum, this indicates that the quarter-to-quarter growth rates are very erratic rather than persistent and confirms the

[9]The maximal lag length was set to 8 for the models for quarter-to-quarter changes and to 4 for the models for year-to-year changes.

TABLE 3. Results for predictability based on univariate information sets: Y-to-Y changes

	Model	P^0_{DK}	$HL_{P_{DK}}$	$\Sigma_{P_{DK}}$
GDP	AR(1)	0.250389	2	0.286220
Pr.Consumption	AR(2)	0.452818	2	0.497080
Gvnt.Consumption	AR(1)	0.039732	2	0.040540
Fixed Inv.	AR(1)	0.192790	2	0.213360
Building Inv.	AR(1)	0.218197	2	0.244920
Exports	AR(2)	0.261251	3	0.377010
Imports	AR(2)	0.262433	2	0.325750

usual wisdom that those quarter-to-quarter rates are incredibly hard to forecast.

A somewhat different picture results from the assessment of year-to-year growth rates. The results are given in Table 3 and visualized in Figure A.2 in the appendix. They show that the annual growth rates are all in all more persistent and exhibit a higher degree of predictability. With the notable exception of government consumption growth, which is virtually unpredictable according to the measure used here also on a year-to-year basis, all time series show estimated *One-Step Predictabilities* between .19 and .45 and *Accumulated Predictabilities* between .21 and .50!

4.2. **Multivariate Information Sets.** Moving from univariate information sets to multivariate information sets including the different leading indicators, we assess the leading indicators' joint ability to improve on the predictabilities of the growth rates of the GDP components. Not to run into degrees of freedom problems when constructing the VAR models, we split the leading indicators in an obvious way into a group of financial variables and one group of survey indicators and construct two different VARs for each GDP components conditioning on the two full groups of indicators respectively. First, consider again the predictability of quarter-to-quarter growth rates. The summary

TABLE 4. Results for predictability based on multivariate information sets: Q-to-Q changes

	Financial-Indicators			
	Model	P^0_{DK}	$HL_{P_{DK}}$	$\Sigma_{P_{DK}}$
GDP	VAR(2)	0.132291	1	0.185070
Pr.Consumption	VAR(2)	0.143981	1	0.180020
Gvnt.Consumption	VAR(2)	0.138355	1	0.153880
Fixed Inv.	VAR(1)	0.125886	4	0.218410
Building Inv.	VAR(2)	0.246204	1	0.265990
Exports	VAR(2)	0.169325	1	0.229150
Imports	VAR(1)	0.120987	4	0.192080
	Survey-Indicators			
	Model	P^0_{DK}	$HL_{P_{DK}}$	$\Sigma_{P_{DK}}$
GDP	VAR(2)	0.311901	1	0.407740
Pr.Consumption	VAR(2)	0.328045	1	0.393800
Gvnt.Consumption	VAR(2)	0.192857	1	0.227460
Fixed Inv.	VAR(2)	0.133386	3	0.219470
Building Inv.	VAR(2)	0.217854	1	0.235970
Exports	VAR(2)	0.174125	1	0.213850
Imports	VAR(2)	0.319627	1	0.400950

statistics for the different predictabilities conditioned on the two different sets of leading indicators are presented in Table 4 and visualized in Figure A.1 in the appendix. Three main conclusions can be derived from these results. First, predictability is significantly increased by both sets of leading indicators – with the notable exception of private consumption and building investment growth – compared to the situation of univariate information sets. Even stronger: The improvement is not only significant but impressively high. Second, in all but one cases the set of survey indicators yield the higher improvement compared to the set of financial variables (no matter if measured by P^0_{DK} or $\Sigma_{P_{DK}}$). The only component, for which this is not true, are fixed investments. Here, financial variables have more predictive power than survey indicators. Finally, the improvements are also impressive for the long forecast horizons. Natural indicators for this fact are higher estimated differences between P^0_{DK} and $\Sigma_{P_{DK}}$ (than can be observed

TABLE 5. Results for predictability based on multivariate information sets: Y-to-Y changes

	Financial-Indicators			
	Model	P^0_{DK}	$HL_{P_{DK}}$	$\Sigma_{P_{DK}}$
GDP	VAR(1)	0.414341	1	0.506540
Pr.Consumption	VAR(1)	0.541972	1	0.645850
Gvnt.Consumption	VAR(1)	0.067487	1	0.092170
Fixed Inv.	VAR(1)	0.404139	2	0.556350
Building Inv.	VAR(1)	0.390286	1	0.525010
Exports	VAR(1)	0.263715	1	0.352460
Imports	VAR(1)	0.482855	1	0.588750
	Survey-Indicators			
	Model	P^0_{DK}	$HL_{P_{DK}}$	$\Sigma_{P_{DK}}$
GDP	VAR(1)	0.440992	1	0.515030
Pr.Consumption	VAR(1)	0.677995	1	0.820970
Gvnt.Consumption	VAR(1)	0.308984	2	0.445550
Fixed Inv.	VAR(1)	0.342037	1	0.411860
Building Inv.	VAR(1)	0.261943	1	0.307670
Exports	VAR(1)	0.162866	1	0.195380
Imports	VAR(1)	0.355835	1	0.433630

for the univariate setting), i.e. more predictability is accumulated at longer forecast horizons.

Turning to the same analysis for the year-to-year growth rates yields a somewhat different picture. A summary of the results is presented in Table 5 and visualized in Figure A.2 in the appendix. While again the point estimates of the predictabilities are higher in the majority of cases, these improvements are mostly not significant due to the wide 90%-confidence bands from the univariate setting. Only in case of government consumption and fixed investments (and building investment for long forecast horizons) a significant improvement can be observed. And also a comparison of the performance of the two groups of leading indicators yields no clear cut answer although there is a tendency for the financial variables to perform better for long forecast horizons.

4.3. **Optimal Information Sets.** To assess in more detail which of the leading indicators account for the main part of the increased predictabilities and to find an "optimal" information set for the prediction of each GDP component, we set up an automated selection algorithm in the spirit of Hoover and Perez's (1999) general-to-specific (GETS) approach[10]. We stick to the separation of survey indicators and financial indicators. The algorithm consists of the following steps:

1. Set up a *n+1*-dimensional VAR[11] including one of the GDP component's growth rate and all n leading indicators from the set of survey indicators (financial indicators) and compute an AIC on basis of the residuals of the equation explaining the GDP component's growth rate only.
2. Set up n different n-dimensional VARs by excluding one of the leading indicators in one of the VARs. Compute an AIC for each of those VARs on basis of the residuals of the equation explaining the GDP component's growth rate only.
3. If none of the exclusions improves the AIC compared to the AIC of the *n+1*-dimensional VAR, stop the algorithm and choose the n indicators as the "optimal" information set. If one or more of the AICs of the $n - dimensional$ VARs are superior to the AIC of the *n+1*-dimensional VAR, exclude the one indicator, whose exclusion yielded the highest improvement for the AIC, permanently from the set of leading indicators and reduce n by one.
4. Repeat steps 2-3 until no further improvement can be achieved or until $n = 0$.

The models, which are eventually selected by this algorithm, are presented in Tables 6 and 7 and visualized in Figures A.3 to A.6[12]. Table 6 summarizes the results for the models based on quarterly data. At first glance it might be puzzling that the predictabilities that are estimated on the basis of the "optimal" information sets are generally smaller than the ones estimated conditionally on the full sets of leading indicators. Hence, how can these "optimal" information sets be optimal then? The crucial point to understand at this place is that the

[10]For a recent exhaustive survey of the entire GETS literature see Campos et al. (2005).

[11]We select the lag order for each VAR on basis of the AIC during the algorithm.

[12]To ease a comparison with the univariate outcomes, we include the latter (with confidence bands) also in these graphs.

predictability statistic has the same properties as e.g. the R^2 in the sense that by including more and more variables into the information set one continuously improves the predictability as the definition of the statistic includes no penalty term for the number of parameters that have to be estimated in the underlying VAR model.[13]

The selected "optimal" sets of leading indicators vary considerably across the different GDP components. First, consider the analysis based on the financial leading indicators. In general, the algorithm selects sparse information sets including only one or two leading indicators (the exception being fixed investment and imports, for which the full information set is chosen). The financial indicator with predictive power for the highest number of components is i^{short} that shows up in all but two information sets. Second, consider the analysis based on survey indicators. Here, none of the "optimal" sets includes all potential survey leading indicators. Whereas $ifoge$ seems to be a good predictor for almost all GDP components, PMI shows up in only one information set. This is what one would expect given the fact that PMI is based on a panel of US purchasing managers rather than managers in Germany. That indicates that although the PMI is often considered as a leading indicator also for the German business cycle this is not justified given our statistical results. Another notable outcome is that CC helps to improve the predictability of private consumption (and aggregate GDP and exports) but is excluded from the other information sets. This is again what one would expect a priori.

[13]For exactly this reason, we decided to base the selection algorithm above on a conventional measure-of-fit rather than on the predictability measures themselves. For it is not quite clear how a penalty term in the definition of predictability should look like.
Note that while the inclusion of more variables into a model automatically improves the predictability, the uncertainty which comes with the estimates of predictability increases, i.e. the confidence bands widen.

TABLE 6. Results for predictability based on "optimal" multivariate information sets: Q-to-Q changes

	Financial-Indicators				
	Model	Indicators	P^0_{DK}	$HL_{P_{DK}}$	$\Sigma_{P_{DK}}$
GDP	VAR(2)	i^{short}, i^{long}	0.116350	1	0.163110
Pr.Consumption	VAR(2)	i^{short}, i^{long}	0.099110	1	0.117470
Gvnt.Consumption	VAR(1)	–	0.099590	1	0.104810
Fixed Inv.	VAR(1)	*all*	0.125550	4	0.217570
Building Inv.	VAR(3)	$\Delta M3$	0.284780	1	0.342570
Exports	VAR(2)	i^{short}	0.095600	2	0.143900
Imports	VAR(1)	*all*	0.122740	4	0.195110
	Survey-Indicators				
	Model	Indicators	P^0_{DK}	$HL_{P_{DK}}$	$\Sigma_{P_{DK}}$
GDP	VAR(3)	$ifoge, CC$	0.374450	2	0.504630
Pr.Consumption	VAR(2)	$ifoge, ifogl, CC$	0.320470	1	0.392050
Gvnt.Consumption	VAR(2)	$ifogl, PMI$	0.178080	1	0.205110
Fixed Inv.	VAR(2)	$ifoge$	0.098660	3	0.161130
Building Inv.	VAR(3)	$ifogl$	0.252250	1	0.279690
Exports	VAR(2)	$ifoge, CC$	0.147570	1	0.172960
Imports	VAR(2)	$ifoge$	0.305690	1	0.374470

The results for the models based on yearly data, which are summarized in Table 7, lead to similar conclusions. P^0_{DK} and $\Sigma_{P_{DK}}$ are again smaller in general compared to the results based on the full sets of indicators. The sets of selected leading indicators show a huge variety also for these models. And in none of the 14 cases are all leading indicators selected for the information set. Furthermore, $ifoge$ is the only indicator that is – with only two exceptions – selected for each information set. In contrast to the results for quarterly data, ΔDAX is selected for five of the seven information sets. Hence, it seems to be a very good leading indicator for most of the components on a yearly basis.

5. Conclusion

In this paper, we have analyzed whether the most commonly used leading indicators include information that helps improving the predictabilities of growth rates of various components of German GDP.

TABLE 7. Results for predictability based on “optimal“ multivariate information sets: Y-to-Y changes

	Model	Indicators	P^0_{DK}	$HL_{P_{DK}}$	$\Sigma_{P_{DK}}$
	Financial-Indicators				
GDP	VAR(1)	$i^{short}, \Delta DAX$	0.42466	1	0.54494
Pr.Consumption	VAR(1)	$i^{short}, i^{long}, \Delta DAX$	0.51351	1	0.66300
Gvnt.Consumption	VAR(1)	–	0.03973	1	0.04054
Fixed Inv.	VAR(1)	i^{short}, i^{long}	0.37668	2	0.53379
Building Inv.	VAR(1)	$\Delta M3, \Delta DAX$	0.35742	1	0.38621
Exports	VAR(1)	$\Delta Dep, \Delta DAX$	0.21970	1	0.25699
Imports	VAR(1)	$\Delta Dep, \Delta DAX$	0.44471	1	0.51229
	Survey-Indicators				
	Model	Indicators	P^0_{DK}	$HL_{P_{DK}}$	$\Sigma_{P_{DK}}$
GDP	VAR(1)	$ifoge$	0.438690	1	0.512860
Pr.Consumption	VAR(1)	$ifoge, ifogl, PMI$	0.678040	1	0.838820
Gvnt.Consumption	VAR(1)	$ifogl$	0.248380	2	0.326460
Fixed Inv.	VAR(1)	$ifoge, ifogl$	0.338210	1	0.403210
Building Inv.	VAR(1)	$ifoge, CC$	0.253030	1	0.288650
Exports	VAR(2)	–	0.261250	2	0.377010
Imports	VAR(1)	$ifoge, ifogl$	0.408140	1	0.511970

To this end, we relied on the concept of predictability as presented in Diebold and Kilian (2001). We analyzed the predictability of quarterly and yearly growth rates of the GDP components.

The following main results can be extracted from our analysis. First, when estimated in a univariate framework the predictability of the quarterly growth rates are virtually zero for any forecast horizon for all GDP components (excluding private consumption and building investments) whereas the yearly growth rates show some degree of predictability for forecast horizons up to 2-4 years. Second, the inclusion of leading indicators in the information set of the forecasting model improves predictability of quarterly growth rates considerably. Furthermore, the set of survey indicators performs better than the set of financial variables in this analysis.

Third, such an improvement is not observable for multivariate models including leading indicators for prediction of the yearly growth rates. In some cases, the leading indicators help to improve predictability for higher forecast horizons. But generally, the confidence intervals for the predictabilities estimated in a univariate framework are very large and the predictabilities are not significantly increased by moving to the multivariate model framework.

Finally, the analysis has shown that the predictability of all macroeconomic time series considered in this paper is very low – not to say virtually zero – also for very short term forecast horizons if the model that is used to forecast the time series is a purely univariate one. Selecting appropriate leading indicators and basing the prediction on a richer information set increases the predictability considerably for the first quarters (years) ahead. This challenges the view of researchers who question the usefulness of "complicated" forecasting models and claim the superiority of simple AR models for forecasting purposes.

What this study does clearly not want to do is to postulate that predictability of time series or the comparison of different forecasting models should exclusively be based on this concept of predictability. Obviously, other methods – such as out-of-sample forecast assessments or others used e.g. in the studies quoted in section 1 – do also yield important insides for these issues. Still, we think that the statistical concepts presented here are a useful enrichment of the "toolbox".

We think that further research on the issue of predictability could concentrate on how to penalize the richness of the underlying model to produce something like an adjusted measure of predictability (analogously to the adjusted measure of fit $\bar{R}^2$). Furthermore, applications could include an assessments of the relative forecast performance of VARs including different macroeconomic variables and univariate models.

References

Anderesen, Torben G., Tim Bollerslev, Francis X. Diebold, and Jin Wu (2004), "Realized Beta: Persistence and Predictability," CFS-Working Paper 2004/16, Center for Financial Studies.

Banerjee, Anindya, and Massimiliano Marcellino (2006), "Are there any reliable leading indicators for US inflation and GDP growth?" *International Journal of Forecasting*, 137–151.

Banerjee, Anindya, Massimiliano Marcellino, and Igor Masten (2003), "Leading indicators for Euro-area inflation and GDP growth," IGIER-Working Paper 235, Innocenzo Gasparini Institute for Economic Research, IGIER.

Barsky, Robert B. (1987), "The Fisher Hypothesis and the Forecastability and Persistence of Inflation," *Journal of Monetary Economics*, 3–24.

Brisson, Marc, Bryan Campbell, and John W. Galbraith (2001), "Forecasting Some Low-Predictability Time Series Using Diffusion Idices," CIRANO-Working Paper 2001s-46, Centre Interuniversitaire de Recherche en Analyse des Organisations.

Campos, Julia, Neil R. Ericsson, and David F. Hendry (2005), "General-to-specific Modeling: An Overview and Selected Bibliography," International Finance Discussion Papers 838.

Cecchetti, S. G., R. S. Chu, and C. Steindel (2000), "The unreliability of inflation indicators," Current issues in economics and finance 4/6.

Diebold, Francis X., and Lutz Kilian (2001), "Measuring Predictability: Theory and Macroeconomic Applications," *Journal of Applied Econometrics*, 16, 657–669.

Fritsche, Ulrich, and Sabine Stephan (2000), "Leading indicators of German business cycles : an assessment of properties," DIW-Discussion Paper 207, Deutsches Institut fr Wirtschaftsforschung, DIW.

Galbraith, John W. (2003), "Content horizons for univariate time-series forecasts," *International Journal of Forecasting*, 43–55.

Galbraith, John W., and Turgut Kisinbay (2005), "Content horizon for conditional variance forecasts," *International Journal of Forecasting*, 249–260.

Granger, C.W.J., and P. Newbold (1986), *Forecasting Economic Time Series*, Academic Press, Orlando,FL, 2nd edition.

Hannan, E.J., and D.S. Poskitt (1988), "Unit canonical correlations between future and past," *Annals of Statistics*, 784–790.

Hansen, G. D. (1985), "Indivisible labor and the business cycle," *Journal of Monetary Economics*, 309–327.

Hoover, Kevin D., and Stephen J. Perez (1999), "Data mining reconsidered: encompassing and the general-to-specific approach to specification search," *The Econometrics Journal*.

Horowitz, J. (2001), "The Bootstrap," in J.J. Heckman and E.E. Leamer, editors, *Handbook of Econometrics, Vol. 5*, North-Holland, Amsterdam.

Jewell, N.P., and P. Bloomfield (1983), "Canonical correlations of past and future for time series: definitions and theory," *Annals of Statistics*, 837–847.

Kholodilin, Konstantin A., and Boriss Siliverstovs (2005), "On the forecasting properties of the alternative leading indicators for the German GDP: recent evidence," DIW-Discussion Paper 522, Deutsches Institut fr Wirtschaftsforschung, DIW.

Kilian, Lutz (1998), "Accounting for lag order uncertainty in autoregressions: the endogenous lag order bootstrap algorithm," *Journal of Time Series Analysis*, 531–548.

Kilian, Lutz (2001), "Impulse response analysis in vector autoregressions with unknown lag order," *Journal of Forecasting*, 20, 161–179.

Runkle, David E. (1987), "Vector Autoregression and Reality," *Journal of Business and Economic Statistics*, 437–442.

Appendix A.

Figure A.1. Predictability based on univariate and full multivariate information sets: Q-to-Q changes

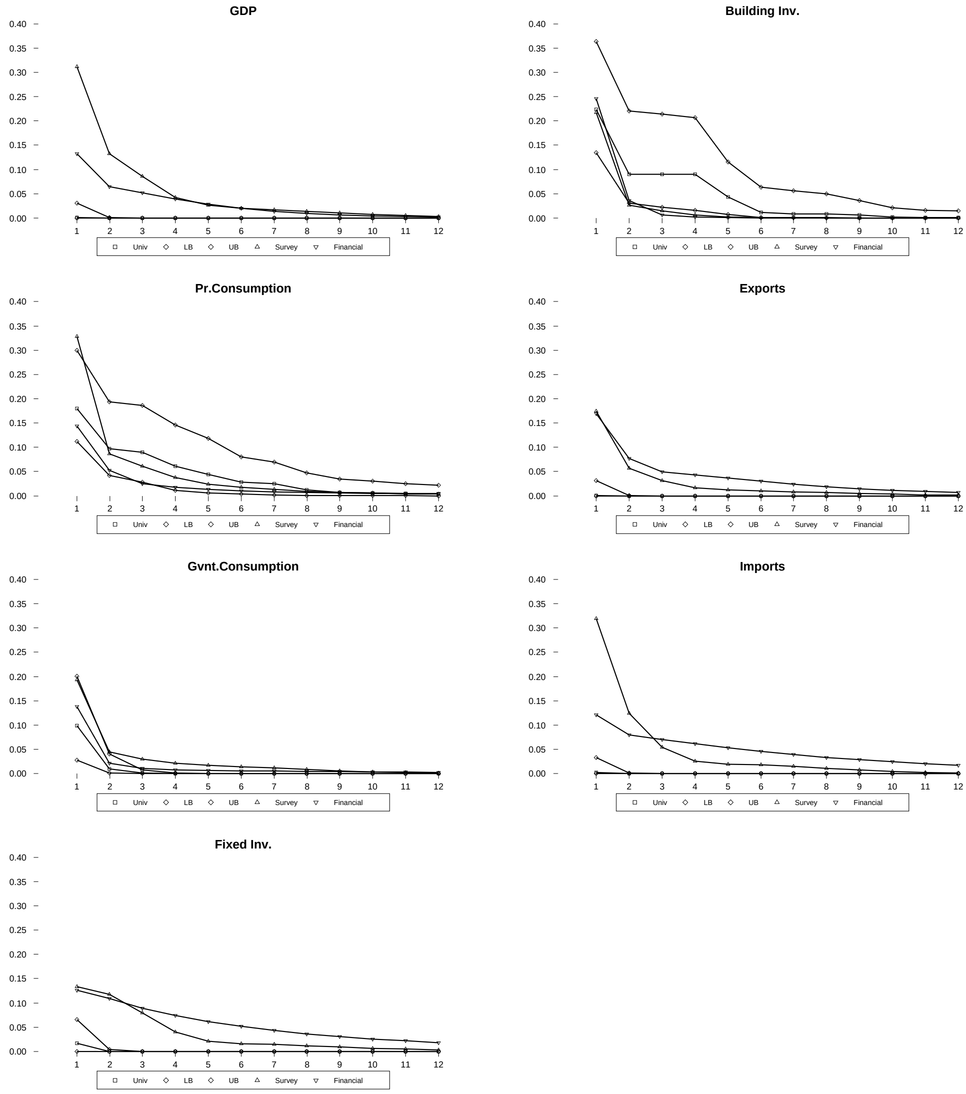

FIGURE A.2. Predictability based on univariate and full multivariate information sets: Y-to-Y changes

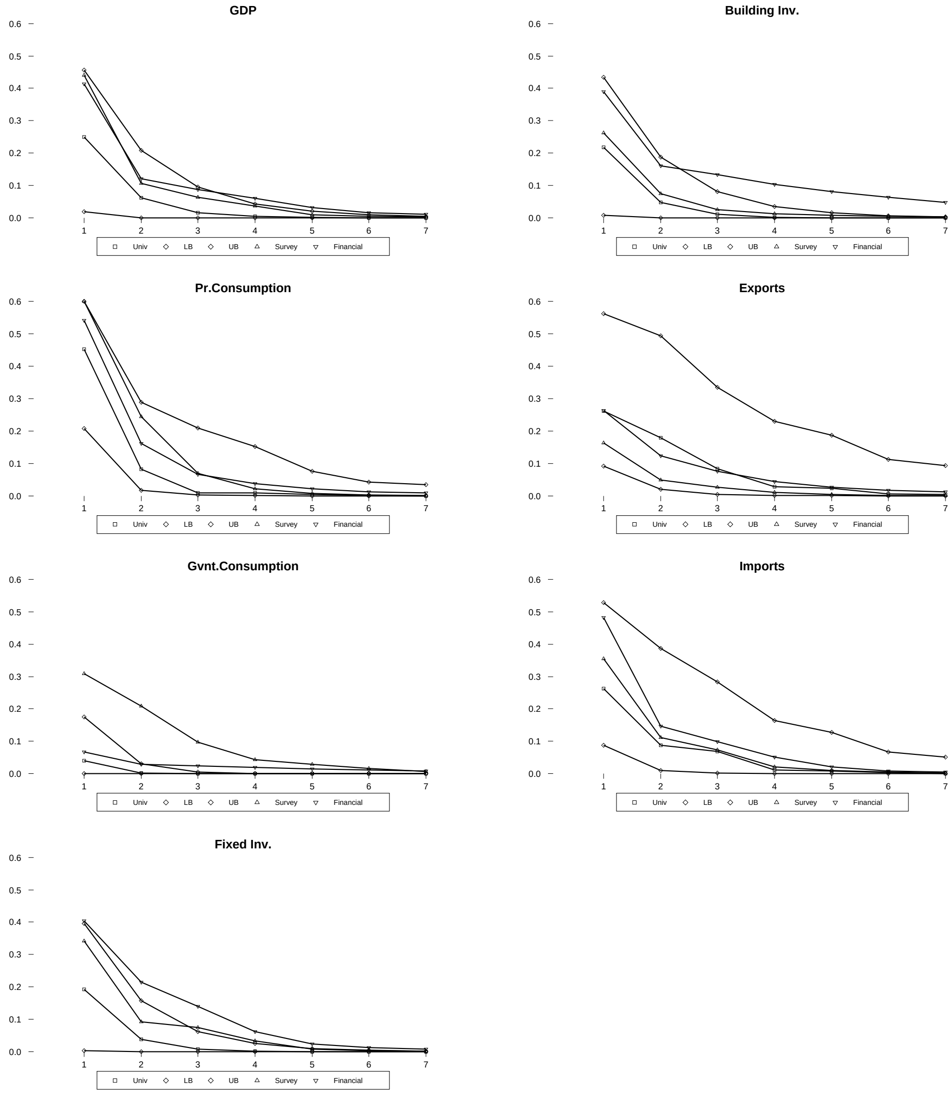

Figure A.3. Predictability based on "optimal" information set of financial leading indicators: Q-to-Q changes

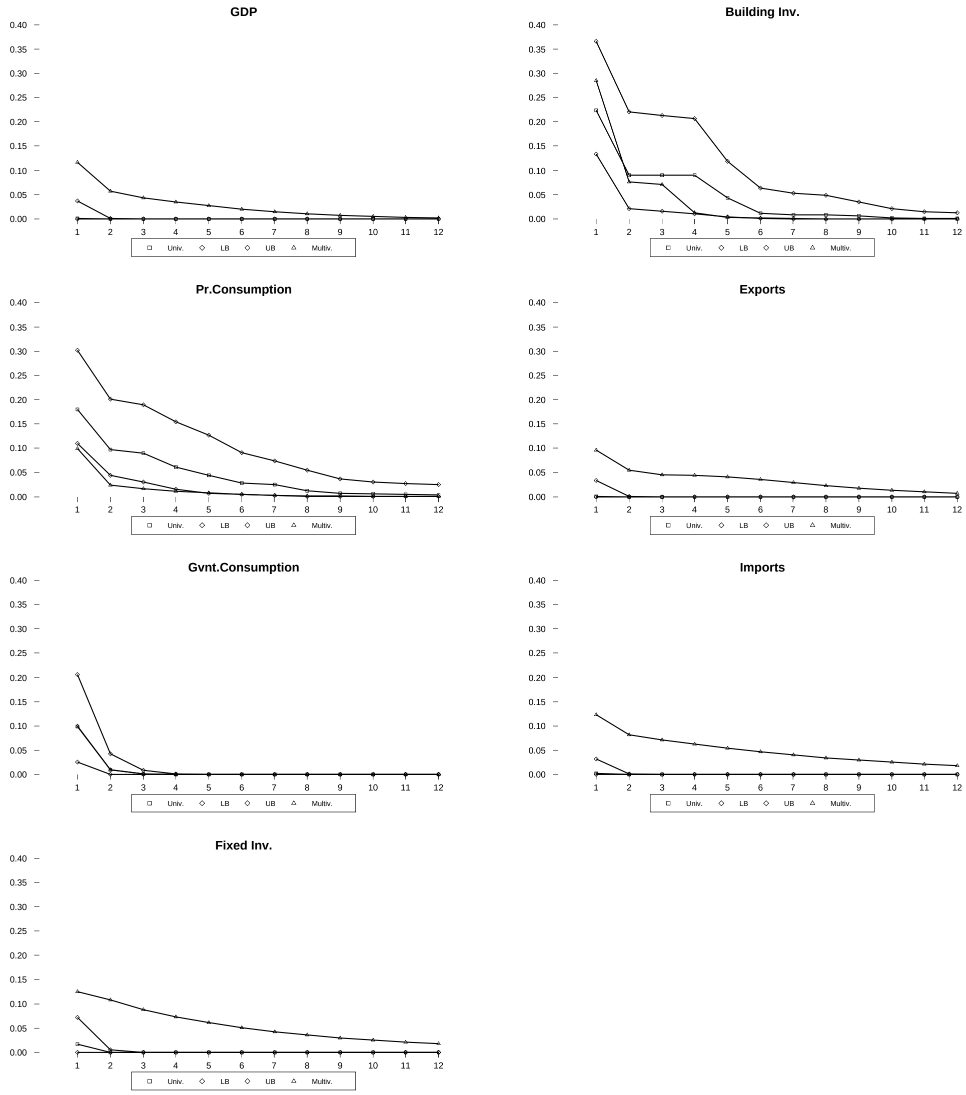

FIGURE A.4. Predictability based on "optimal" information set of survey leading indicators: Q-to-Q changes

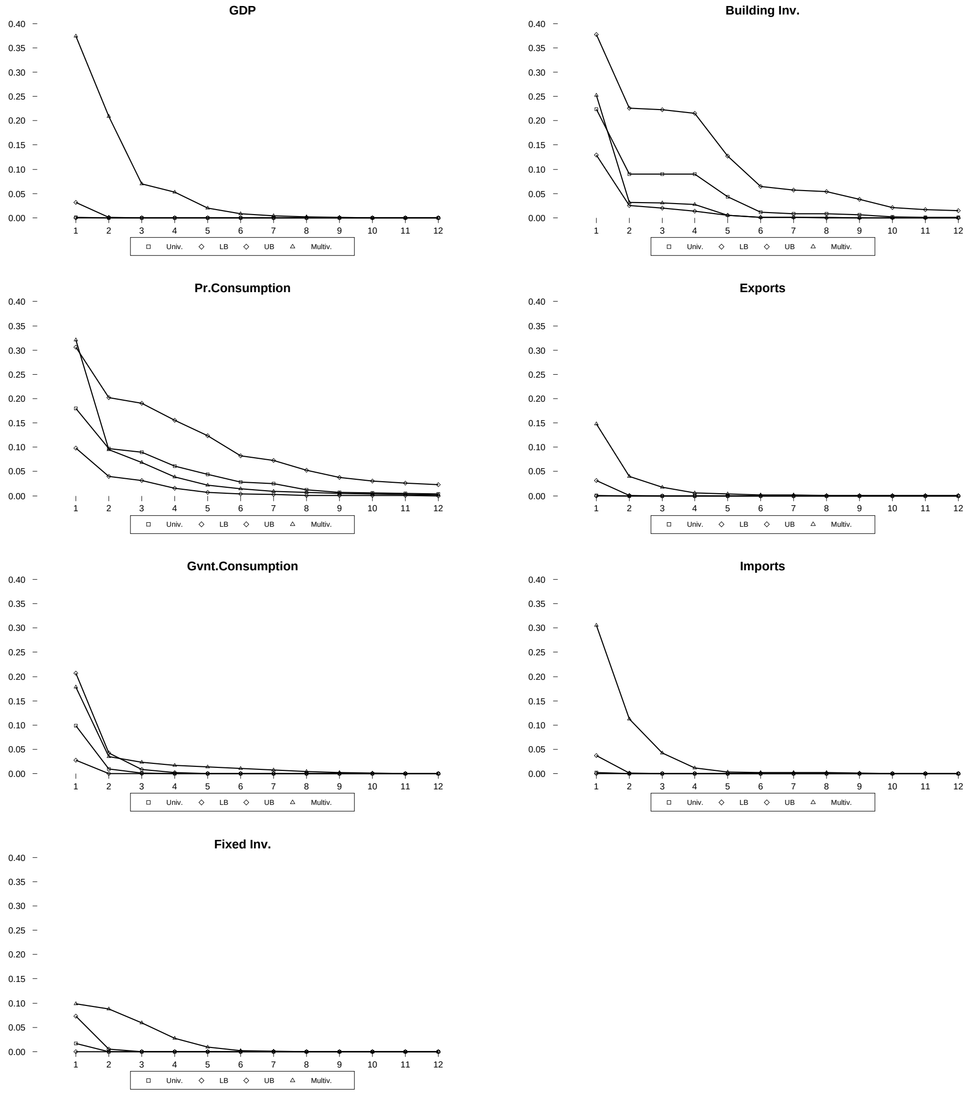

FIGURE A.5. Predictability based on "optimal" information set of financial leading indicators: Y-to-Y changes

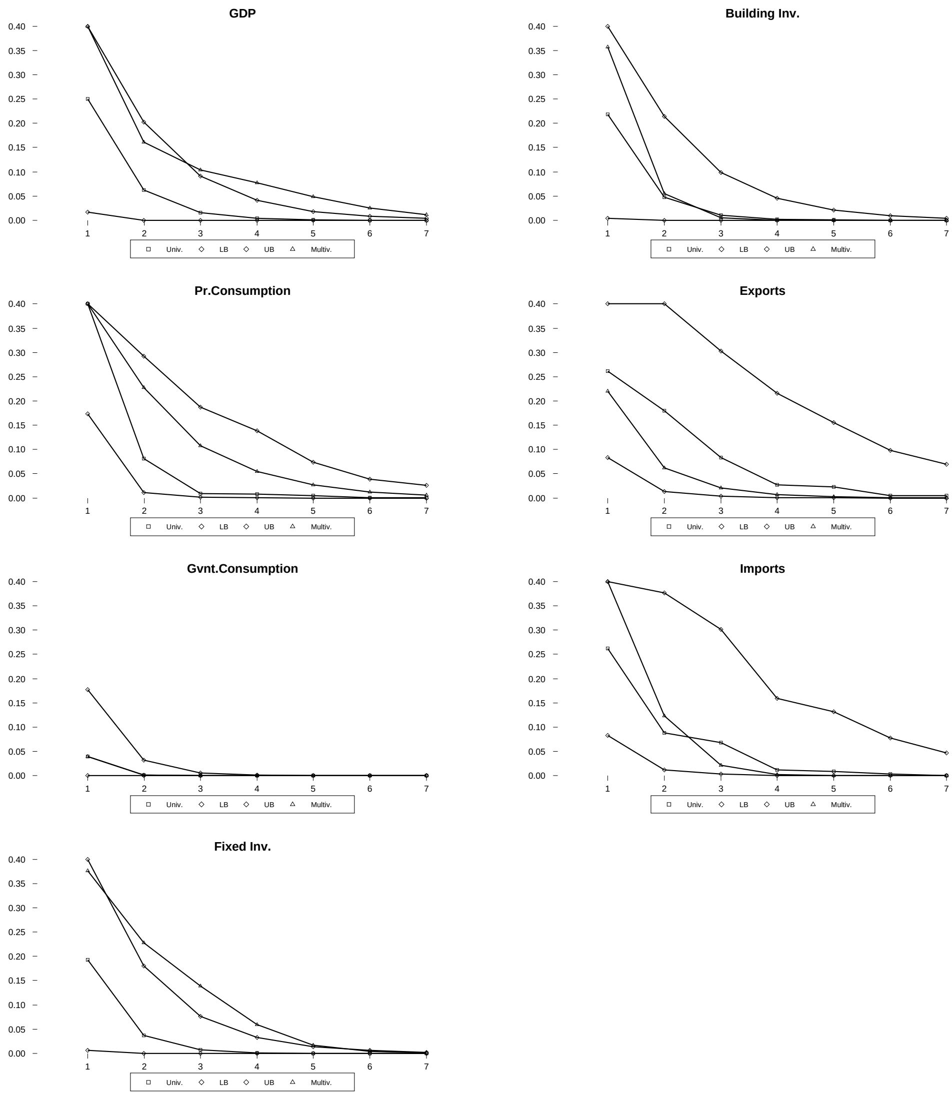

Figure A.6. Predictability based on "optimal" information set of survey leading indicators: Y-to-Y changes