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VAR modelling of the euro area GDP on the basis of principal component analysis

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"VAR modelling of the euro area GDP on the basis of principal component analysis"

By Nikolaos Sdrakas and Cedric Viguie

ABSTRACT:

This study outlines how Principal Component technique can be useful in the short-run economic analysis and forecasting of euro area GDP growth. With reference to a previous work, we examined a restricted vector autoregressive (VAR) model based on selected components from industry and consumer confidence indicators of Business and Consumer surveys (BCS) to forecast the quarterly year-on-year growth of GDP in the euro area. One of the main conclusions was that this restricted VAR model outperforms a single autoregressive model in the short term forecasting, since we excluded all noise variables, which do not help to explain GDP growth .

In this paper we focus on VAR and autoregressive estimations based on a more deep approach. Their combination with principal component analysis is considered, which will remove the noise factor from the various shocks among variables (i.e. extracting only the common trend).

The derived forecasts of these new models are compared with those of the old VAR. The predictive performance of VAR and autoregressive models has been improved by including the first principal component based in all questions from the four main domains (Industry, Consumption, Construction, Retail Trade).

BACKGROUND AND AIM OF THE PAPER

With reference to previous work we assessed univariate autoregressive models in the short-run economic analysis and forecasting by using traditional tools with different data (quarterly national accounts, business surveys). In particular, we have shown that autoregressive single equations models, can perform reasonably well in terms of forecasting ability, when they are compared with more complicated econometric models, i.e. the BUSYIII model developed by DG ECFIN (see progress report presented on Workshop on BCS, Brussels, November 2002). Moreover, the inclusion of the Economic Sentiment Indicator (ESI) in this baseline model clearly improved the results, showing that people's opinions (expectations) derived from the business and consumer surveys could lead by 1 quarter the quantitative data (GDP growth).

In a latter stage ,our objective was the specification of more complicated models, like Vector Autoregressive Models (VAR). We examined a vector autoregressive (VAR) model based on the BCS results to forecast the quarterly year-on-year growth of GDP in the euro area for two quarter ahead. In particular, the four main components[1] of the

[1] The Industrial (BCSINDU), the Retail Trade (BCSRETA), the Construction (BCSBUIL) and the Consumer Confidence Indicator (BCSCONS) are the four variables introduced.

ESI were initially considered. The results from the Granger Causality test led us to reduce the VAR model to four variables; Retail trade confidence Indicator was excluded (see Annex 1). According to the results of the Diebold Mariano test, we showed that the restricted VAR did not outperform a single equation model in the short run. Even thought the results from the shock analysis (see Annex 2) were interesting to understand the structural shocks hitting the European economy, some improvements had to be made.

In a more recent work, we focused on a VAR approach based on a more deep approach. The specific components of the industry and consumer confidence indicators are considered[2]. The two components of the construction confidence indicator have excluded, due to non stationarity and high volatility. The derived forecasts of the new restricted VAR model are compared with those of the single autoregressive model. The predictive of VAR models has been improved by excluding all the noise variables (balances of opinions) ,whose past values cannot explain GDP growth. In particular, we selected specific components of the industrial (indu) and consumer (cons) confidence indicator, who might be leading indicators for GDP growth. The order books (indu2), production expectations (indu5), financial situation over the next 12 months (cons2), unemployment over the next months (cons7) and savings over the next months (cons11) are the five variables introduced (see Annex 3). Moreover, we showed that this restricted VAR model (see Annex 4) outperformed a single autoregressive model in the short term forecasting.

In this paper we focus on VAR and autoregressive estimations based on the principal component analysis, which will remove the noise factor from the various shocks among variables (i.e. extracting only the common trend). The derived forecasts of these new models are compared with those of the old VAR.

1. Data analysis

The real GDP series for the euro area was taken from the quarterly national accounts in an non seasonally adjusted form and was transformed into quarterly year-on-year growth (GDPg hereafter). The series is available from 1991Q1 to 2002Q4. The balances of opinions from the monthly business and consumer surveys concerning euro area countries were used. In particular, all the questions (272) from the four main domains (Industry, Consumption, Construction, Retail Trade) were considered[3]. Before introducing the balances of opinion within the models, we had to transfer these monthly data into quarterly data i.e. taking the three month average.

[2] The three components of the Industrial (indu) and the four of the Consumer (cons) Confidence Indicator are based on the balances of opinion in the EU harmonised questionnaire: order books (indu2), stocks (indu4), production expectations (indu5), financial situation over the next 12 months (cons2), general economic situation over the next 12 months (cons4), unemployment over the next months (cons7) and savings over the next months (cons11) are the seven variables introduced.

[3] http://europa.eu.int/comm/economy_finance/indicators/businessandconsumersurveys_en.htm

1.1 Principal component analysis

In order to reduce the dimensionality of the data set and to remove all the idiosyncratic shocks in each variable, the technique of principal component analysis was used. Principal component analysis (PCA) involves a mathematical procedure that transforms a number of (possibly) correlated variables into a (smaller) number of uncorrelated variables called *principal components*. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible.

According to our empirical results derived from SAS software programme, the first principal component (PC) explained more than 30% of the total variance.

1.2 Unit roots

With a constant term, two tests- Augmented Dickey-Fuller, Philips-Perron-rejected the null hypothesis of a unit root in the GDPg. The first principal component had to be converted into quarterly year-on-year differences (d) in order to become stationary.

1.3 Cross-correlation

Cross correlation analysis was used in order to test whether the quarterly year-on-year differences of the first principal component (x) can be considered as a leading indicator of GDPg (y). There is evidence to suggest that x appears to be a leading indicator for y at the first lag (see Table 1)

Table 1: Cross Correlations of GDPg (y) and PCd (x)

	y, x(-i)	y, x(+i)
i	lag	lead
0	0.70	0.70
1	0.77	0.47
2	0.64	0.17
3	0.45	-0.19
4	0.22	-0.47

2. Model analysis

2.1 AR model selection and estimation

A first step was to estimate a model for y by using its own past values as predictors. We started the estimation process with nine lags as explanatory variables, reducing step-wise the number of lags. Finally, a model with five lags was chosen. Excluding the non-significant lags in this model (i.e. lags 2 and 3) resulted in the new fitted model.
Since the baseline model is a function of the past values of GDP growth, quarterly y-o-y differences of the first Principal Component (x) were included. Since x is a leading indicator of y we estimated a model for y, consisting of its own past values at lags 1, 4 and 5, and x at the first lag. OLS regression was used as estimation method. The estimated sample period is 1993Q2-2002Q4 (see Table 2).

Table 2: AR estimates

Sample(adjusted): 1993:2 2002:4
Standard errors in ( ) & t-statistics in [ ]

Equations/ Variables	y
y(-1)	0.47 (0.14) [3.5]
y(-4)	-0.32 (0.13) [-2.55]
y(-5)	0.43 (0.14) [3.13]
x(-1)	0.08 (0.02) [3.46]
C	0.74 (0.22) [3.31]
Adj. R-squared	0.77

2.2 VAR model selection and estimation

A standard VAR with two variables is presented below:

$$Y_t = c + \sum_{i=1}^{p} \Theta Y_{t-i} + \varepsilon_t$$

where c is a constant and $Y_t = \begin{bmatrix} y_t \\ x_t \end{bmatrix}$

The sample period begins in 1992Q1 and finishes in 2002Q4. As Y_t is stationary, Zellner's theorem allows as to estimate the system with OLS equation by equation. According to the Schwarz Information Criterion based on the likelihood ratio, the optimal lag number is 3. However, for reasons of parsimony a second model was estimated excluding also the 2nd and 3rd lag (see Table 3).

Table 3: VAR estimates

Sample(adjusted): 1992:2 2002:4
Standard errors in ( ) & t-statistics in [ ]

Equations/ Variables	x	y
x(-1)	1.06	0.07
	(0.09)	(0.01)
	[11.1]	[3.95]
y(-1)	-1.82	0.41
	(0.66)	(0.12)
	[-2.74]	[3.42]
C	3.35	0.99
	(1.36)	(0.25)
	[2.47]	[3.95]
Adj. R-squared	0.81	0.69

1.5 AR roots

The following test reports the inverse roots of the characteristic AR polynomial; see Lutkepohl (1991). The estimated VAR is stable (stationary) if all roots have modulus less than one and lie outside the unit circle. The following table shows that the restricted VAR satisfies the stability condition, since no root lies outside the unit circle.

Table 4: VAR stability condition check

Roots of Characteristic Polynomial
Endogenous variables: x, y
Exogenous variables: C
Lag specification: 1

Root	Modulus
0.749861 - 0.169375i	0.768752
0.749861 + 0.169375i	0.768752

3. Forecasting

With the new VAR model dynamic short-term forecasts of GDP growth were calculated (1 quarter following the release of the quarterly national accounts).

In order to forecast the quarterly year-on-year GDP growth one quarter ahead from the last release of national accounts-the current quarter (t)-, we used the new VAR based on the first principal component. This form allows us to take into account the information available at an early stage from the business surveys. For instance, at the moment the study was conducted, the business surveys are available up to 2003Q1 whereas the national accounts are estimated up to 2002Q4.

Concerning the forecast of GDP growth for the next quarter (t +1) – one quarter ahead from the last release of the national accounts, the simulation is based on the new form of the VAR.

According to the results, the GDP growth would continue to rise in 2003Q1 by 0.82%. This compares with a forecast of 1.06% derived from the new VAR.

In order to make an ex-post forecast evaluation with 2 quarters ahead, the two models (VAR versus autoregressive) were re-estimated again. The simulation started in 2000Q1by adding one observation each time and keeping the same forecasting horizon. Thus, we came up with eleven dynamic simulations, the last one ending in 2002Q4.

Table 5 shows the Root Mean Squared Errors (RMSE) of the two models as well as those of the old VAR model based on selected components from industry and consumer confidence indicators.

One way to compare the three alternative forecasts is to calculate a Relative Root Mean Squared Forecasting Error (RRMSFE), which is the ratio between the root mean squared forecasting error of the restricted VAR(1) model and the root mean squared forecasting error of the simple autoregressive model. A RRMSFE lower than 1 implies that the out-of-sample performance of the new VAR is better than the performance of the old VAR model and that of the autoregressive model. We then use the Diebold-Mariano test[4] to see whether the RRMSFE is significantly different from 1.

Table 5:	**RMSE**			**RRMSFE**	**RRMSFE**
Simulation Period	old VAR	AR	new VAR	new VAR vs AR	new VAR vs old VAR
2000Q1-2000Q2	1.32	0.84	1.42	1.69 (6.28) [0.1]	1.08 (0.48) [0.71]
2000Q2-2000Q3	0.4	0.72	0.35	0.48 (-1.03) [0.49]	0.87 (-0.7) [0.61]
2000Q3-2000Q4	0.13	0.97	0.91	0.94 (-0.54) [0.68]	7.02 (2.58) [0.24]
2000Q4-2001Q1	1.53	0.32	0.35	1.09 (8.56) [0.07]	0.23 (-1.01) [0.5]
2001Q1-2001Q2	1.21	0.49	0.37	0.76 (-1.24) [0.43]	0.31 (-4.14) [0.15]
2001Q2-2001Q3	0.78	0.89	0.1	0.12 (-9.32) [0.07]	0.13 (-11.35) [0.06]
2001Q3-2001Q4	1.08	0.69	0.27	0.39 (-1.02) [0.49]	0.25 (-1.13) [0.46]
2001Q4-2002Q1	1.36	0.72	0.52	0.73 (-1.67) (0.34)	0.39 (-1.02) (0.49)
2002Q1-2002Q2	0.85	0.25	0.55	2.16 (1.2) [0.44]	0.65 (-1.2) [0.44]
2002Q2-2002Q3	0.41	0.4	0.56	1.42 (3.37) [0.18]	1.38 (1.13) [0.46]
2002Q3-2002Q4		0.32	0.25	0.79 (-0.76) [0.59]	
Average RMSE	0.9	0.6	0.52		

Note: Diebold-Mariano t statistics are provided in parentheses. P-values are provided in brackets, given that the critical level is 5%. One star indicates that the RRMSFE is not significantly different from 1 at 1%.

The outcomes of the Diebold Mariano test indicate that in all cases the RRMSFE is significantly different from 1 (see Table 3). As we can see the new VAR model outperforms both a single equation model and the old VAR in the short run.

4. Conclusion and future perspectives

This note has outlined how Principal Component technique can be useful in the short-run economic analysis and forecasting of euro area GDP growth. With reference to a previous work, the predictive performance of VAR and autoregressive models has been improved by including the first principal component based in all questions from the four main domains (Industry, Consumption, Construction, Retail Trade). Moreover, we showed that the new VAR model outperforms a single autoregressive model in the short term forecasting.

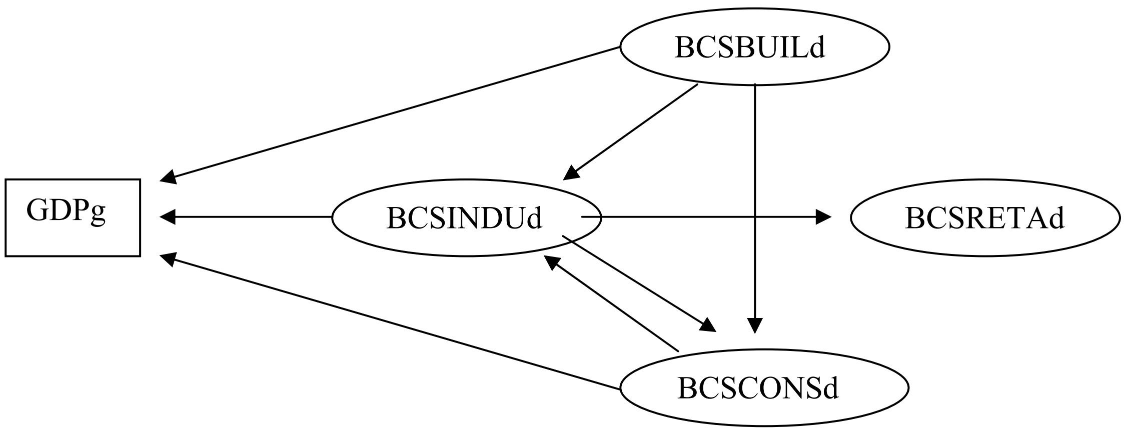
[4] The aim of this test is to see whether or not it is possible to discriminate between two forecasting models. Let e_{1t} and e_{2t} denote alternative forecast errors and $d_t = (e_{1t})^2 - (e_{2t})^2$. The Diebold-Mariano test for equal RMSEs is simply formed as a t-statistic on a constant α in the regression $d_t = \alpha + \varepsilon_t$. In general the closer the RRMSFE is to 1, the more likely the Diebold-Mariano test accepts the hypothesis of same forecast performance. However, this link is not so direct due to a correction of the variance which is implemented in the Diebold Mariano test. For reference of the Diebold-Mariano test see T.E. Clark (1999).

Even if the first principal component removes all the noise factors from the various shocks among the variables to the other components, some improvements have to be made. A distinction between leading, lagging and coincident variables with respect to euro area GDP growth is necessary in order to enhance the forecasting performance of our models. Firstly, A combination of a common factor analysis, which will include only the leading variables and VAR models should be considered in future work. Secondly, concerning all the lagging variables, a phase shift procedure should be performed in combination with the PCA, before we introduce the first principal component within an autoregressive model.

Annex 1

A.1.1 Granger causality tests

Among the five variables introduced in the VAR(1), we implemented the tests of nested hypotheses for all the permutations of Y. The non-instantaneous causal links obtained from these tests are summarised in the following chart:



N.B: the links are accepted at a significance level of 5%.

The past values of the differences in industry (BCSINDUd), construction (BCSBUILd) and consumer confidence indicator (BCSCONSd) help to forecast the GDP growth at the current time.

These causality tests led us to reduce the VAR model to four variables: GDPg, BCSINDUd, BCSCONSd, BCSBUILd. We estimated the optimal lag order for this restricted VAR to be 1. Moreover, the residuals of this new VAR are uncorellated.

Annex 2

Analysis of shocks

The shock identification is based on the Choleski decomposition. If the spread of a shock to the others variables depends on the sequence of the variables in VAR(1), the ordering is partly arbitrary. In our case, we want to understand the effects of shocks to every variable on the GDP growth. The sequence of the variables is the following: BCSINDUd, BCSBUILd, BCSCONSd, GDPg.

A2.1 Variance decomposition

The following table shows the decomposition of the forecast-error variance of GDP growth from the VAR model. We decomposed the various contributions of shocks to BCSINDUd, BCSBUILd, BCSCONSd and GDPg. The shocks to GDPg are the innovations, which arise outside the model.

Table 1:Variance Decomposition of GDP growth:relative contribution of the different types of shocks (in percent).

Period	S.E.	BCSINDUd	BCSBUILd	BCSCONSd	GDPg
1*	0.7	6.2	0.7	6.1	87.0
2	0.9	21.4	5.7	10.3	62.5
3	1.1	29.0	11.9	12.9	46.2
4	1.2	30.8	16.3	14.5	38.3
5	1.2	30.5	19.5	15.4	34.5
6	1.3	29.6	22.1	15.7	32.6
7	1.3	28.8	24.1	15.6	31.5
8	1.3	28.1	25.7	15.4	30.8
9	1.3	27.6	27.0	15.1	30.3
10	1.3	27.3	27.9	14.9	29.9
15	1.4	26.5	29.9	14.8	28.8
20	1.4	26.6	30.0	14.7	28.6

* Quarter 1 is the contemporaneous quarter

Since all the four types of shocks are uncorrelated by assumption, the proportion of the GDP growth variance caused by the sum of the four shocks is always equal to 100 percents.

The coefficients of this decomposition stabilised after fifteen quarters. In the first period- the contemporaneous one -, the balance of opinion related to BCSINDUd explains 6% of the forecast error variance of the output growth, BCSBUILd 1% and BCSCONSd 6%. GDPg explains 87% of its own forecast error.

However, the weight of GDPg decreases from the second period and the influence of BCSBUILd and BCSINDUd increases markedly. In the long run, GDPg is therefore determined mainly by BCSBUILd and BCSINDUd.

In order to determine the effect that these variables have on GDP growth, the impulse response functions were computed.

A2.2 Impulse responses

This table shows the dynamic responses of GDPg to one unit of standard deviation shock in the estimated equations (see Appendix 1) associated with each variable. All entries are multiplied by 100. Quarter 1 is the contemporaneous quarter.

Table 2: Impulse responses of the VAR(1) model. Responses GDP growth to residuals shocks from each variable

Period	BCSINDUd	BCSBUILd	BCSCONSd	GDPg
1	0.2	-0.1	-0.2	0.7
2	0.4	0.2	-0.2	0.2
3	0.4	0.3	-0.2	0.0
4	0.3	0.3	-0.2	0.0
5	0.2	0.3	-0.2	0.0
6	0.1	0.2	-0.1	0.0
7	0.0	0.2	-0.1	0.0
8	0.0	0.2	0.0	0.0
9	0.0	0.2	0.0	0.0
10	0.0	0.2	0.0	0.0
11	0.0	0.1	0.0	0.0
12	0.0	0.1	0.1	0.0
13	0.0	0.1	0.0	0.0
14	0.0	0.1	0.0	0.0
15	0.0	0.1	0.0	0.0
16	0.0	0.0	0.0	0.0

From this table we can observe the direction of the system. These data shows that shocks to BCSINDUd have an effect on GDPg during six periods, on BCSBUIL during fifteen. This means that the stronger BCSINDUd effect on GDP growth disappears after six quarters- more than one year-, but the weaker BCSBUILd effect is more persistent.

Annex 3

A.3.1 Pairwise Granger Causality Tests

In general, this test allows us to test whether an endogenous variable can be treated as exogenous. This criterion has been satisfied in all equations, after performing the test. However, since we are mainly interesting in estimating GDPg, the test is limited on the first block of variables with GDPg being the dependent variable. The output in the table below displays χ^2 (Wald) statistics for the significance (critical level is 5%) of each of the other lagged endogenous variables in that equation.

Table1: VAR Pairwise Granger Causality

Dependent variable: GDPg

Exclude	Chi-sq	df	Prob.
cons2d	4.75	1	0.0
cons4d	1.12	1	0.3
cons7d	16.51	1	0.0
cons11d	15.27	1	0.0
indu2d	11.25	1	0.0
indu4d	0.01	1	0.9
indu5d	21.94	1	0.0

It is fairly obvious that cons4d and indu4d should be excluded from the equation. These causality tests led us to reduce the VAR model to six variables: GDPg, cons2d, cons7d, cons11d, indu2d, indu5d. (see VAR estimation in Appendix1).We estimated the optimal lag order for this restricted VAR to be 1. Moreover, the residuals of this new VAR are uncorellated.

A.3.2 Cross Correlation

Cross correlation analysis was used in order to test whether the quarterly year-on-year differences (d) of the balances of opinion, can be considered as leading Indicators of GDPg. It is fairly obvious from the Tables illustrated below that cons11d and GDPg are coincident. In addition, there is some evidence to suggest that cons2d, cons7d, indu2d and indu5d are leading indicators for GDPg at the first lag.

Table 2.1: Cross Correlations of cons2d and GDPg

	GDPg, cons2d(-i)	GDPg, cons2d(+i)
i	lag	lead
0	0.61	0.61
1	0.61	0.42
2	0.50	0.22
3	0.42	-0.10
4	0.23	-0.35

Table 2.2: Cross Correlations of cons7d and GDPg

	GDPg, cons7d(-i)	GDPg, cons7d(+i)
i	lag	lead
0	-0.52	-0.52
1	-0.59	-0.39
2	-0.50	-0.19
3	-0.34	0.08
4	-0.18	0.31

Table 2.3: Cross Correlations of cons11d and GDPg

	GDPg, cons11d(-i)	GDPg, cons11d(+i)
i	lag	lead
0	0.69	0.69
1	0.68	0.59
2	0.51	0.39
3	0.43	0.07
4	0.27	-0.12

Table 2.4: Cross Correlations of indu2d and GDPg

	GDPg, indu2d(-i)	GDPg, indu2d(+i)
i	lag	lead
0	0.56	0.56
1	0.58	0.40
2	0.47	0.15
3	0.32	-0.17
4	0.14	-0.44

Table 2.5: Cross Correlations of indu5d and GDPg

	GDPg, indu5d(-i)	GDPg, indu5d(+i)
i	lag	lead
0	0.40	0.40
1	0.60	0.12
2	0.55	-0.13
3	0.42	-0.42
4	0.21	-0.57

Annex 4

A.4.1 VAR estimation

This is the estimation of VAR based on five balances of opinion from business and consumer surveys and the GDP growth on the euro area.

Sample(adjusted): 1992:2 2002:3
Standard errors in ( ) & t-statistics in [ ]

Equations/ Variables	GDPg	cons2d	cons7d	cons11d	indu2d	indu5d
GDPd(-1)	0.42	-0.41	1.60	0.17	-0.96	-1.69
	(0.1)	(0.25)	(0.81)	(0.3)	(0.75)	(0.85)
	[4.3]	[-1.6]	[2.0]	[0.6]	[-1.28]	[-2.0]
cons2d(-1)	-0.52	0.39	-0.69	-0.18	-0.27	-0.18
	(0.11)	(0.29)	(0.94)	(0.34)	(0.87)	(0.99)
	[-4.5]	[1.3]	[-0.7]	[-0.5]	[-0.3]	[-0.2]
cons7d(-1)	-0.09	-0.03	0.50	-0.06	0.19	0.15
	(0.02)	(0.05)	(0.16)	(0.06)	(0.15)	(0.17)
	[-4.3]	[-0.6]	[3.0]	[-1.0]	[1.2]	[0.9]
cons11d(-1)	0.48	0.31	-0.43	0.67	1.01	0.96
	(0.09)	(0.22)	(0.7)	(0.26)	(0.65)	(0.74)
	[5.6]	[1.4]	[-0.6]	[2.6]	[1.6]	[1.3]
indu2d(-1)	-0.08	-0.06	0.22	-0.04	0.18	-0.41
	(0.02)	(0.05)	(0.15)	(0.05)	(0.14)	(0.16)
	[-4.4]	[-1.2]	[1.5]	[-0.7]	[1.3]	[-2.6]
indu5d(-1)	0.12	0.18	-0.79	0.10	1.34	1.51
	(0.02)	(0.05)	(0.16)	(0.06)	(0.15)	(0.17)
	[6.4]	[3.7]	[-5.0]	[1.8]	[9.1]	[9.0]
	1.05	0.91	-3.68	-0.27	2.18	3.53
C	(0.22)	(0.56)	(1.81)	(0.66)	(1.68)	(1.91)
	[4.7]	[1.6]	[-2.0]	[-0.4]	[1.3]	[1.9]
Adj. R-squared	0.83	0.83	0.90	0.70	0.94	0.84

cons2: financial situation over next 12 months
cons7: unemployment next 12 months
cons11: savings next 12 months
indu2: order books
indu5: production expectations

A.4.2 Diebold-Mariano test

Table 3:	RMSE		RRMSFE
Simulation Period	VAR(1)	autoregressive	VAR(1)* vs autoregressive model
2000Q1-2000Q2	1.32	1.35	0.98 (0.46) [0.73]
2000Q2-2000Q3	0.4	0.52	0.78 (1.55) [0.36]
2000Q3-2000Q4	0.13	1.08	0.13 (2.48) [0.24]
2000Q4-2001Q1	1.53	1.05	1.46 (-0.78) [0.58]
2001Q1-2001Q2	1.21	1.41	0.86 (0.66) [0.63]
2001Q2-2001Q3	0.78	0.31	2.51 (-3.35) [0.18]
2001Q3-2001Q4	1.08	0.39	2.77 (-1.08) [0.47]
2001Q4-2002Q1	1.36	1.38	0.99* (0.01) (0.99)
2002Q1-2002Q2	0.85	1.58	0.54 (1.05) [0.49]
2002Q2-2002Q3	0.41	0.54	0.76 (0.36) [0.78]
Average RMSE	0.9	0.96	

* It is a restricted VAR based on cons2 cons7 cons11 indu2 indu5
cons2: financial situation over next 12 months
cons7: unemployment next 12 months
cons11: savings next 12 months
indu2: order books
indu5: production expectations

Note: Diebold-Mariano t statistics are provided in parentheses. P-values are provided in brackets, given that the critical level is 5%. One star indicates that the RRMSFE is not significantly different from 1 at 1%.

The outcomes of the Diebold Mariano test indicate that in almost all cases the RRMSFE is significantly different from 1 (see Table 3). As we can see the new restricted VAR model outperforms a single equation model in the short run.

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