The information content of financial variables for forecasting output and prices: results from Switzerland

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Introduction

Central banks need reliable forecasts of output and prices to conduct monetary policy. Forecasts of prices are important because central banks aim at delivering price stability in the long run. Forecasts of output are necessary because, under certain conditions, central banks may find it helpful to influence the business cycle and to stabilise output in the short run. Several financial variables have long been used as important information variables to forecast output and prices. Traditionally, a monetary aggregate, like M0, M1 or M2, has been the key variable for many central banks. Several authors recently documented the decline in the forecasting ability of money, especially in the case of the United States.[1] Thus, the relation between money and prices and between money and output has become loose. At the same time, many of these authors suggested that interest rates and interest rate spreads dominate money as information variables.[2] However, it is also possible that other financial variables and asset prices contain important information to forecast prices and output. This is especially of interest because of the large movements in financial variables, such as exchange rates and stock market prices, in recent years. Movements of asset prices and financial variables may reflect expectations of market participants. These expectations usually have a strong impact on changes in output and prices. Movements of asset prices and financial variables, however, may also be the consequence of large portfolio shifts and financial innovations. Such shifts in the financial structure of a country are important because they signal possible changes in the money demand function. Generally, large movements in financial variables may lower the information content of money and render a monetary policy based on monetary aggregates more difficult to pursue. Exploiting the information from other financial variables can alleviate this problem.

In 1992, the Swiss National Bank started to pursue a more flexible monetary policy by announcing a medium-term target for its monetary base. This allows the use of a broader spectrum of information variables. The monetary policy of the Swiss National Bank may not exclusively depend on the development of the monetary base, particularly in the short run. Nevertheless, the Swiss National Bank considers the monetary base as the most important information variable for prices in the long run and therefore formulates a medium target for base money. In the short run, alternative indicators become more important for policy decisions, independently of whether the Swiss National Bank follows a policy of monetary targeting or a policy of inflation targeting.[3]

The aim of this paper is therefore to evaluate in what respect financial variables other than monetary aggregates help to forecast output and prices. As pointed out by Sims (1972) and by Friedman and Kuttner (1992), a financial variable is a useful information variable for forecasting output and prices if fluctuations in this variable, not only predict fluctuations in prices and output in general, but also movements which are not foreseeable from past fluctuations in output and prices. As

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1 See, for example, the influential papers by Friedman and Kuttner (1992, 1993 and 1996) and Friedman (1996).

2 See also Bernanke (1990).

3 Some countries started to use a monetary conditions index as an information variable. Lengwiler (1997) shows that such an index does not deliver superior information compared to a monetary aggregate in Switzerland.

long as a variable "Granger'' causes money and prices, it can be used by the central bank as an information variable, independently of the exact nature of the causation. However, an information variable is most useful if its predictive power remains stable over a long period of time.

In the sections below, I use vectorautoregression methodology in order to analyse the information content of various variables and systems. Besides the monetary aggregate M2, the analysis is applied to a broad set of different financial variables,[4] including the bond interest rate, the spread between the short and the long-run interest rate, the trade-weighted nominal exchange rate index and the stock market index. The focus is thus to check what type of financial variable can potentially be important. Further research could, for example, look closer at a set of different exchange rates or at different interest rates.

The analysis shows that money and the exchange rate index are the most important information variables of those considered. Money (M2) is especially helpful in predicting output. The systems including money keep their forecasting superiority over time, although it has recently become more difficult to predict output. The exchange rate index has a predictive content about prices. However, this forecasting information erodes over time, so that, at the end of the considered samples, forecasts of prices based only on past output and prices outperform all other forecasts.

The paper is organised as follows: In Section 1, the in-sample predictive content of the set of financial variables is analysed by considering variance decompositions. Section 2 looks at the out-of-sample forecasting ability. In Section 3, the change of the predictive content is analysed and the last section concludes.

1. In-sample predictive content

This section analyses the in-sample information content of variables for predicting output and prices by estimating vectorautoregressions (VAR) of various systems.[5] I start by considering the integration order of the variables included in this study. The augmented Dickey-Fuller test and the Phillips-Perron test indicate that all variables are integrated of order I(1), with the exception of the spread between the long and the short-run interest rate. Although not completely clear-cut, the tests point toward stationarity of the spread.[6] VARs with integrated variables are usually estimated with differenced data. However, differencing leads to a loss of information if a cointegrating relation is present.[7] Instead, VARs in levels preserve possible cointegrating relationships among the variables without explicitly imposing a specific cointegration vector. Therefore, the Johansen procedure is applied for the basic systems considered below in order to test for cointegration between the variables. The results indicate that, indeed, the null hypothesis of no cointegration between the variables of the systems considered in the subsequent analysis can be rejected.[8]

Since there is possible cointegration among the variables, I estimate different vectorautoregressions with variables in levels. As pointed out by Sims, Watson and Stock (1990) and

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4 Note, however, that the set of financial variables available for analysis is rather limited in Switzerland.

5 A methodological alternative would be to use vector error correction models.

6 The results of the unit root tests are not reported here. For trending variables, the regressions of the test include a constant term and a time trend. For non-trending variables, i.e., interest rates and spreads, only a constant is included.

7 See Sims, Watson and Stock (1990) and Hamilton (1994).

8 The cointegration results are not reported here. They are in line with the findings from other studies based on similar data. See, for example, Flury and Spörndli (1994).

Hamilton (1994), standard Granger causality tests (F-tests on all lags of the same variable) are not valid if a VAR consisting of I(1) variables is estimated in levels. However, no statistical problems exist for the computation of variance decompositions. Furthermore, as put forward by Thoma and Gray (1994), F-statistics can be misleading indicators of causality, because the effect of one variable on another may be transmitted through a third variable. In addition, F-tests only refer to the one-quarter-ahead prediction while variance decompositions allow for predictions over a longer horizon. Variance decompositions are capable of measuring the quantity of the predictive content of a variable whereas F-tests only indicate whether a variable has any information content at all.[9]

The regressions used in this section of the paper take the form:

$$x_t = D(L)x_{t-1} + \varepsilon_t \tag{1}$$

where x is the vector of variables of the system. All variables, except for the interest rate and the interest spread, are measured in logarithms.[10] ε is a vector of serially uncorrelated reduced-form disturbances and $D(L)$ is a matrix polynomial in the lag operator L. The number of lags in the regression is determined by the Schwarz information criterion. According to this criterion, the optimal lag length for all systems is 2. The variance decomposition is computed by inverting the VAR to a vector moving average representation:

$$x_t = C(L)\varepsilon_t \tag{2}$$

and by orthogonalising the reduced-form residuals ε_t:

$$A_0 u_t = \varepsilon_t \tag{3}$$

where $E(u_t u_t') = I$. The orthogonalisation is done by a Cholesky decomposition, where the ordering corresponds to the ordering of the variables in the vector x. Thus, A_0 corresponds to the Cholesky decomposition of $\Omega = E(\varepsilon_t \varepsilon_t')$.[11]

In the following, I try to determine the information content of the financial variables for forecasting output and prices. To begin with, I consider the widely used 3-variable VAR consisting of logs of output y, prices p, and money m, so that the vector x corresponds to $x = [y\ p\ m]$.[12] In this study, money is represented by the aggregate M2. This aggregate is used by the Swiss National Bank as one indicator among others for predicting future price and output movements. The aggregate M2 is, however, not the intermediate target of the Swiss National Bank. Rather, the Bank sets a medium-term target for the monetary base. Since the demand for base money was hit by several structural shocks in the late 1980s, I prefer to use a broader aggregate in this study in order to examine the forecasting power of money on output and prices.[13] The $y\ p\ m$ VAR concentrates on the importance of money as a predictor of prices and output and does not consider any other financial variable. It therefore directly tests the monetarist hypothesis what movements in money are followed by subsequent movements in

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9 See, for example, Friedman and Kuttner (1996).

10 Small letters indicate variables in logs.

11 For the estimation of the VAR, a constant term is included.

12 For a discussion and survey of VAR studies, see e.g., Todd (1990).

13 See Rich (1997) for a complete analysis of the Swiss monetary policy in the post Bretton Woods period.

output and prices. However, it is important to note that the money component of the orthogonalised shocks (money innovations) of this VAR does not necessarily represent monetary policy shocks. Rather, the variance decomposition shows how important money innovations are for forecasting prices and output, independently of the true structural shocks, which cause unexpected changes in the variables of the system.

Table 1

Variance decomposition: *y p m* VAR

Variable	Horizon	Innovation		
		y	*p*	*M*
y	4	96 (1)	1 (0)	3 (1)
	8	93 (2)	1 (0)	6 (2)
	12	75 (5)	1 (1)	24 (5)
	16	62 (6)	1 (1)	37 (6)
	20	58 (7)	3 (1)	39 (7)
P	4	8 (4)	89 (4)	3 (1)
	8	23 (6)	70 (6)	7 (1)
	12	32 (7)	63 (7)	5 (1)
	16	34 (7)	60 (7)	6 (1)
	20	33 (7)	56 (7)	11 (1)

Note: In this and the following tables, standard errors (given in parentheses) were calculated using Runkle's (1987) bootstrapping method based on 200 replications.

Table 1 presents the variance decomposition for output and prices. All data used in this study consists of quarterly observations over the sample period from 1974:1 through 1996:4, so that the study covers the period of flexible exchange rates. The orthogonalisation of the system is made in the order of the vector and places output first, prices second, and money third. The standard errors are computed by using the bootstrap method by using the bootstrap method by Runkle (1987). Money innovations explain little of the forecast error variance up to a horizon of 8 quarters. However, for longer horizons, money becomes more important: At a 12-quarter horizon, money explains 25% of the output variance and at a 20-quarter horizon it explains almost 40%. This demonstrates clearly that money is an important predictor of real output, in spite of a substantial time lag between innovation and effect. The results are less favourable for the use of money as a useful information variable for prices. Money innovations explain very little of the forecast error variance of prices. Even at a 20-quarter horizon, only about 10% of the forecast error variance can be attributed to money innovations.

In the following, I expand the VAR analysis by including additional variables to find out whether other financial variables and asset prices contain information, which is not already included the monetary aggregate M2, to forecast prices and output. I am specifically interested in finding out whether the financial variable itself is important for the forecast error variance and whether the inclusion of the financial variable changes the relative forecasting power of M2. Therefore, I run a series of 4-variable VARs by including other financial variables, each of them in addition to M2. Thereby, I concentrate on 4 variables: the bond rate *i* (long-term interest rate), the trade-weighted nominal exchange rate index *e*, the SBC stock market index *a*, and the spread between the long and the short-run interest rate *s*.[14]

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[14] All data are from the Swiss National Bank data base. Output is measured by real GDP. Prices reflect the consumer price index. The monetary aggregate is M2. The bond rate corresponds to the long-term interest rate on government bonds. The

Table 2

Variance decomposition: *y p m i* VAR

Variable	Horizon	Innovation			
		y	*p*	*m*	*i*
Y	4	96 (1)	1 (0)	3 (1)	0 (0)
	8	92 (2)	1 (0)	5 (1)	2 (0)
	12	76 (5)	1 (1)	17 (4)	6 (1)
	16	66 (6)	1 (1)	25 (5)	8 (2)
	20	62 (6)	2 (1)	28 (6)	8 (2)
P	4	9 (5)	88 (5)	3 (1)	0 (0)
	8	24 (7)	70 (7)	6 (1)	0 (0)
	12	32 (8)	63 (8)	5 (1)	0 (0)
	16	35 (8)	59 (8)	5 (1)	1 (0)
	20	34 (8)	56 (8)	7 (2)	3 (1)

First, consider the *y p m i* VAR in Table 2. The inclusion of the bond rate *i* in the VAR slightly diminishes the forecasting importance of money for output. The bond rate itself is of little significance. When combined, *m* and *i* explain a smaller amount of the forecast error variance than *m* alone does in the *y p m* VAR. Of course, the ordering of the orthogonalisation favours *m* over *i* in the relative forecasting power. This is of some importance because of the relatively high correlation of the reduced-form residuals between *m* and *i*. However, *i* adds little new information to forecasting output. With respect to prices, the results are similar. The bond rate is unimportant for the forecast error variance of prices at all horizons considered.[15]

Table 3

Variance decomposition: *y p m e* VAR

Variable	Horizon	Innovation			
		y	*p*	*m*	*e*
Y	4	96 (1)	0 (0)	4 (1)	0 (0)
	8	92 (2)	1 (0)	4 (1)	3 (1)
	12	76 (4)	2 (1)	9 (3)	12 (3)
	16	65 (5)	2 (1)	15 (4)	18 (4)
	20	61 (6)	2 (1)	15 (4)	22 (5)
P	4	10 (4)	85 (4)	5 (1)	0 (0)
	8	30 (6)	48 (6)	19 (4)	3 (1)
	12	39 (6)	32 (6)	22 (4)	7 (2)
	16	40 (6)	26 (5)	19 (4)	15 (3)
	20	37 (6)	22 (5)	16 (3)	25 (5)

short-term rate is the 3-month interest rate. The exchange rate index is trade-weighted and nominal. The stock market index is computed by the Swiss Bank Corporation.

15 Similar results for both output and prices are obtained when the short-run interest rate is used instead of the long-run interest rate.

Second, I substitute the exchange rate index *e* for the interest rate *i* in the VAR. The results are reported in Table 3. The inclusion of *e* diminishes the forecasting importance of *m* for output. In addition, the exchange rate index *e* explains a substantial fraction of the output forecast error variance for horizons longer than 12 quarters. Furthermore, the inclusion of *e* drastically increases the significance of money for forecasting prices even at shorter horizons. The exchange rate index itself is also able to explain a large fraction of the forecast error variance of prices for horizons over 12 quarters. The financial variables *m* and *e* together are thus important information variables for forecasting prices.

Table 4

Variance decomposition: *y p m a* VAR

Variable	Horizon	Innovation			
		Y	*p*	*m*	*a*
y	4	97 (1)	0 (0)	2 (1)	1 (0)
	8	87 (3)	0 (0)	7 (2)	6 (2)
	12	67 (6)	1 (1)	23 (5)	9 (3)
	16	56 (7)	1 (1)	34 (6)	9 (3)
	20	53 (7)	2 (2)	37 (6)	8 (3)
P	4	11 (4)	85 (5)	1 (0)	3 (1)
	8	31 (7)	54 (8)	1 (1)	14 (4)
	12	38 (8)	38 (8)	1 (0)	23 (6)
	16	37 (8)	30 (7)	5 (2)	28 (6)
	20	33 (8)	26 (7)	11 (3)	30 (6)

Table 5

Variance decomposition: *y p m s* VAR

Variable	Horizon	Innovation			
		Y	*p*	*m*	*s*
y	4	97 (1)	0 (0)	3 (1)	0 (0)
	8	93 (2)	1 (0)	6 (2)	0 (0)
	12	77 (5)	1 (0)	22 (5)	0 (0)
	16	65 (7)	1 (1)	33 (7)	1 (0)
	20	61 (7)	2 (1)	36 (7)	1 (0)
P	4	7 (4)	90 (4)	2 (1)	1 (0)
	8	25 (6)	65 (6)	3 (1)	7 (2)
	12	32 (7)	54 (6)	2 (1)	12 (3)
	16	31 (7)	48 (6)	7 (1)	14 (3)
	20	28 (7)	44 (6)	15 (3)	13 (3)

Third, in place of the exchange rate index, the SBC stock market index *a* is included in the VAR. The results of the *y p m a* VAR are shown in Table 4. The asset price index *a* itself explains only little of the output forecast error variance and leaves the fraction of the variance explained by money almost unchanged compared to the *y p m* VAR. The inclusion of the stock market index does not improve the forecast power of money for prices. However, the stock market index alone seems to explain a large fraction of the forecast error variance of prices. Compared to the *y p m e* VAR, *m* and *a* together explain less of the price forecast error variance than *m* and *e*.

Fourth, I consider the *y p m s* VAR, where the spread between the long and the short-run interest rate *s* is included (Table 5). With respect to output, the spread has almost no forecasting power at all. With respect to prices, the spread is more important than the bond rate, but less important than both the exchange rate index and the stock market index. Overall, the spread does not seem to be a very informative variable about future output and prices.[16]

Since the results indicate that *e* and *a* may be important, especially for forecasting prices, I run VARs which include either *e* or *a* but exclude *m*. The results of the *y p e* VAR are represented in Table 6. Compared to the *y p m* VAR, *e* explains approximately the same fraction of the output variance as does *m*. In addition, *e* has strong predictive content for prices for horizons beyond 10 quarters. On the contrary, *a* explains little of the forecast error variance for either output or prices (*y p a* VAR in Table 7). This indicates that the stock market index is of lesser importance for forecasting prices and output.

Table 6

Variance decomposition: *y p e* VAR

Variable	Horizon	Innovation		
		Y	*p*	*e*
Y	4	96 (1)	2 (1)	2 (1)
	8	80 (5)	5 (2)	15 (4)
	12	67 (7)	6 (3)	27 (6)
	16	59 (8)	6 (3)	35 (7)
	20	54 (9)	6 (3)	40 (8)
P	4	7 (5)	93 (5)	0 (0)
	8	30 (7)	63 (7)	7 (2)
	12	42 (6)	37 (6)	21 (4)
	16	42 (6)	24 (4)	34 (6)
	20	39 (7)	18 (3)	44 (7)

Table 7

Variance decomposition: *y p a* VAR

Variable	Horizon	Innovation		
		Y	*p*	*e*
y	4	100 (0)	0 (0)	0 (0)
	8	99 (0)	1 (0)	0 (0)
	12	98 (0)	2 (0)	0 (0)
	16	97 (1)	2 (1)	1 (0)
	20	95 (1)	4 (1)	1 (0)
P	4	20 (6)	77 (7)	3 (1)
	8	49 (8)	44 (8)	7 (2)
	12	63 (7)	29 (7)	8 (2)
	16	70 (7)	22 (6)	8 (2)
	20	74 (7)	19 (5)	7 (2)

[16] Note that the spread is I(0). Thus, by estimating the VAR in levels, the information content of the spread may be underestimated.

The results from these variance decompositions lead to the conclusion that both money and the exchange rate index are important information variables for forecasting output and prices. They dominate the other financial variables, i.e., the bond rate, the spread and the stock market index as predictors of output and prices at all horizons. Money and the exchange rate index are especially helpful for forecasting at horizons over 8 to 10 quarters. For forecasts up to 8 quarters, the time series of output and prices seem to contain the most predictive information themselves.

2. Out-of-sample forecasts

Variance decompositions reflect the in-sample fit of vectorautoregressions and thus concern the in-sample forecasting ability. However, superior in-sample forecasting ability does not automatically mean superior out-of-sample forecasting ability. As put forward by Bernanke (1990) and by Thoma and Gray (1994), the ultimate decision about the usefulness of a variable as an information variable must come from its ability to forecast out of sample. Consequently, I test the out-of-sample forecasting ability with respect to output and prices of different VAR systems by applying a variation of the method used in Thoma and Gray (1994). The out-of-sample forecasting ability is measured by the root mean square error of forecasts at different horizons. The statistic for the 4-quarter horizon is computed as follows: The VAR is estimated over the period 1974:3–1984:2 (40 observations). Using the estimated coefficients and dynamic forecasting techniques, forecasts of output and prices in 1985:2 are generated (4-quarter-ahead forecasts). Then, the sample is shifted one quarter ahead to cover the period 1974:4–1984:3. The VAR is now re-estimated, so that forecasts for 1985:3 can be generated. This procedure is continued until the forecasts reach the end of the sample (1996:4). The generated series of 4-quarter-ahead forecasts and the actual data can be used in order to compute the root mean squared forecast error. The same method is applied to compute 8 and 12-quarter horizon forecasts and the corresponding root mean square errors (RMSE). The RMSE of the different VAR systems can then be used to evaluate forecasting ability. The smaller the RMSE, the more information is contained in the variables of the VAR considered.

Table 8

RMSE of 4-quarter-ahead forecasts

VAR system	RMSE for y	RMSE for p
$y\ p$	0.0265	0.0206
$Y\ p\ m$	0.0180	0.0197
$y\ p\ m\ l$	0.0205	0.0213
$y\ p\ m\ e$	0.0175	0.0165
$y\ p\ m\ a$	0.0199	0.0240
$y\ p\ m\ s$	0.0181	0.0197
$y\ p\ e$	0.0276	0.0194
$y\ p\ a$	0.0350	0.0184

Table 8 reports the results for the 4-quarter forecasting horizon. I consider all the VAR systems which were analysed for the in-sample forecasting ability. Furthermore, I include the two variable $y\ p$ VAR in the analysis. This VAR can be used as a direct benchmark in order to find out whether the inclusion of a specific information variable helps to reduce the RMSE for output and prices. Such a comparison was not possible in the analysis of the variance decompositions of Section 1.

The inclusion of M2 in the VAR system ($y\ p\ m$ VAR) helps to reduce the RMSE of output by almost a third, but the RMSE of prices is only changed to a small extent. Thus, money contains useful information about output over the next 4 quarters. With respect to the forecasts of prices, the information content of M2 is small. Next, I increase the VAR system to contain 4 variables by adding each time another financial variable in addition to M2. The *y p m i* VAR brings no improvement over the *y p m* VAR. Thus, the bond rate does not dominate M2 as an information variable over the 4-quarter horizon. The results are similar for the *y p m a* VAR and the *y p m s* VAR. Whereas the *y p m a* VAR worsens the results, the *y p m s* VAR achieves almost the same RMSEs as the *y p m* VAR. On the contrary, the *y p m e* VAR improves the forecasts for both output and inflation. The decline in the RMSE for output is only small, whereas for prices the reduction is quite large (approximately 15%). Thus, the exchange rate index again seems to be an important information variable, especially for prices. In order to find out whether the exchange rate index contains forecast information independently of M2, I compute the RMSEs from the *y p e* VAR, where M2 is dropped from the system. The RMSE for both output and prices becomes larger, indicating that the exchange rate index delivers the best forecasting information (for the 4-quarter horizon) if combined with a monetary aggregate.[17]

Table 9

RMSE of 8-quarter-ahead forecasts

VAR system	RMSE for *y*	RMSE for *p*
y p	0.0564	0.0402
Y p m	0.0275	0.0429
y p m I	0.0330	0.0499
y p m e	0.0302	0.0384
y p m a	0.0320	0.0515
y p m s	0.0304	0.0425
y p e	0.0563	0.0336
y p a	0.0696	0.0484

Table 10

RMSE of 12-quarter-ahead forecasts

VAR system	RMSE for *y*	RMSE for *p*
y p	0.0863	0.0604
y p m	0.0439	0.0656
y p m I	0.0455	0.0753
y p m e	0.0510	0.0593
y p m a	0.0507	0.0783
y p m s	0.0520	0.0633
y p e	0.0867	0.0461
y p a	0.0980	0.0854

Table 9 shows the findings for the 8-quarter horizon from the same VAR systems. The *y p m* VAR performs best with respect to output. The *y p m* VAR cuts the RMSE for output in half compared to the *y p* VAR. Furthermore, all 4-variable systems have bigger RMSEs for *y* than the *y p m* VAR. As for the 4-quarter horizon, the inclusion the exchange rate index (*y p m e* VAR) improves the forecast for prices. However, the best result is achieved if M2 is dropped from the VAR, which confirms the importance of exchange rates for forecasting prices.

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17 As a reference, the results from the *y p a* VAR are also included in Tables 8 to 10.

In Table 10, the results for the 12-quarter horizon are presented. They are similar and consistent with the findings for the other horizons: The *y p m* VAR performs best with respect to output and the *y p e* VAR achieves the best out-of-sample forecasts for prices. The out-of-sample forecast analysis shows that money (M2) and the exchange rate index *e* are the two most important information variables of all the financial variables considered. Interest rates, interest rate spreads, and stock market prices do not seem to incorporate superior information, which is not already reflected by either money or exchange rates. The results of this section are consistent with those obtained from the variance decomposition. In both experiments, money and the exchange rate turned out to be the most important information variables. However, the variance decompositions indicated that these variables are only of interest for medium and long-term forecasts, whereas the out-of-sample forecasting exercise shows that money and exchange rates are also important for short horizon forecasts (e.g., over 4 quarters). The exercise carried out in this section also shows that expanding the VAR to include more variables does not generally improve the forecasting ability and may actually cause a decline in the out-of-sample forecasting power. This confirms the findings by Thoma and Gray (1994).

3. The change of the predictive content

The information content of the variables may change over time because of structural shocks to the economy. So far, the analysis did not take up this problem. In this section, I check whether the forecasting power of the variables changes over time. Thereby, I concentrate on the 3 systems, which proved to be most valuable for forecasting prices and output, namely on the 3-variable VARs *y p m* and *y p e* and the 4-variable VAR *y p m e*. I use a rolling regression methodology explained in detail below. This kind of technique was used, for example, in Thoma and Gray (1994), Friedman (1996), and Friedman and Kuttner (1996).

I start by considering the in-sample forecasting ability and compute variance decompositions for the 3 systems. I chose a series of consecutive sample periods each consisting of 40 observations (10 years). The first sample starts in 1974:3 and ends in 1984:2. For each sample, the fraction of the forecast error variance is computed for both output and prices over the 8 and the 12-quarter horizons. The 4-quarter horizon is not reported, because the fraction of the forecast error variance explained by financial variables is generally very small. The percentages of the forecast error variance due to financial variables are shown in Figures 1 to 3. The horizontal line indicates the last observation of the estimation sample.

The results from the *y p m* VAR are plotted in Figure 1. Generally, the importance of money for the forecast error variance is very sensitive to the sample period. Shifting the end of the sample towards 1989 increases the importance of M2 strongly. Up to 60% of the forecast error variance of output is explained by money even at the 8-quarter horizon. However, if the end of the sample is expanded beyond 1994, money explains only a small fraction of the forecast error variance, indicating that the predictive content of money has become smaller. The results are similar for prices. Shifting the sample forward to 1992 sharply increases the fraction of the forecast error variance explained by M2. Shifting the sample beyond 1993 causes a deterioration of the forecasting ability.

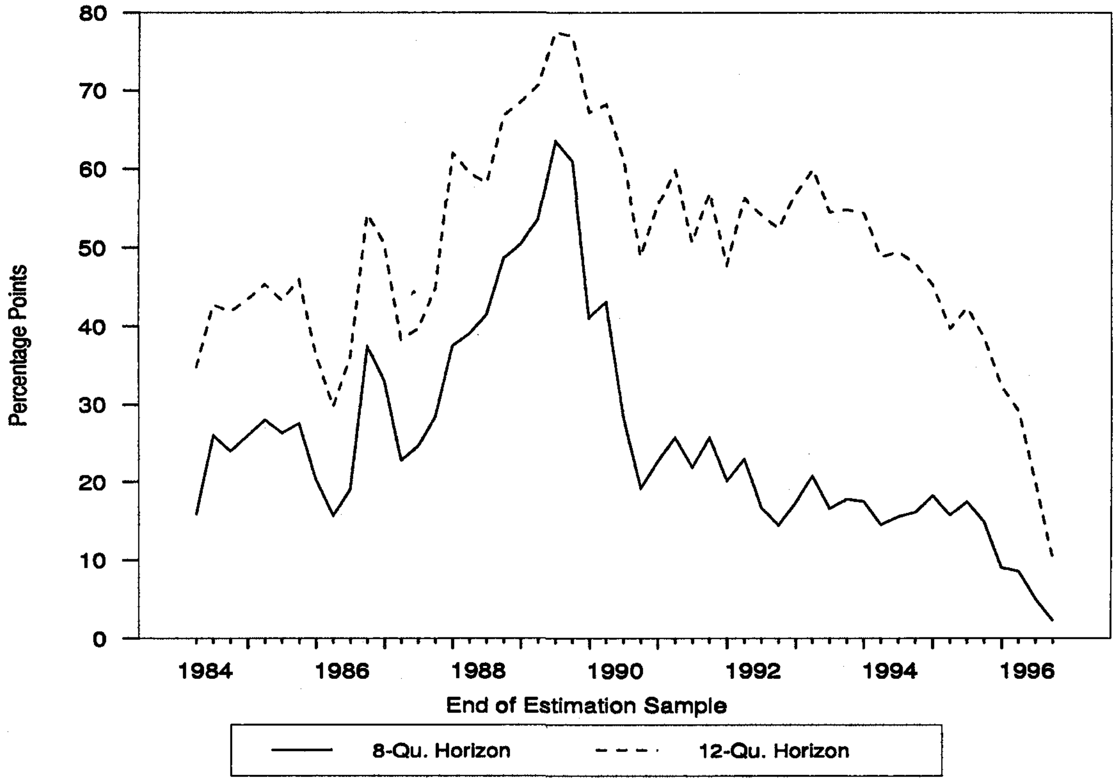
In Figure 2, the results from the *y p e* VAR are shown. It can be observed that the exchange rate index contains important information for samples ending before 1986. In these samples, large fractions of the forecast error variance of both output and prices are due to innovations in the exchange rate index. However, the predictive content of the exchange rate index sharply deteriorates if the sample ends after 1986.

Figure 3 presents the findings for the *y p m e* VAR. The most striking result is that the information content of money is deteriorating to a lesser extent for samples ending after 1989 if the exchange rate is included in the system. The importance of the exchange rate itself generally declines if the sample is shifted forward. However, the forecasting ability of money is much more robust if the

Figure 1

y p m **VAR**

A: Forecast error variance of output explained by money



B: Forecast error variance of prices explained by money

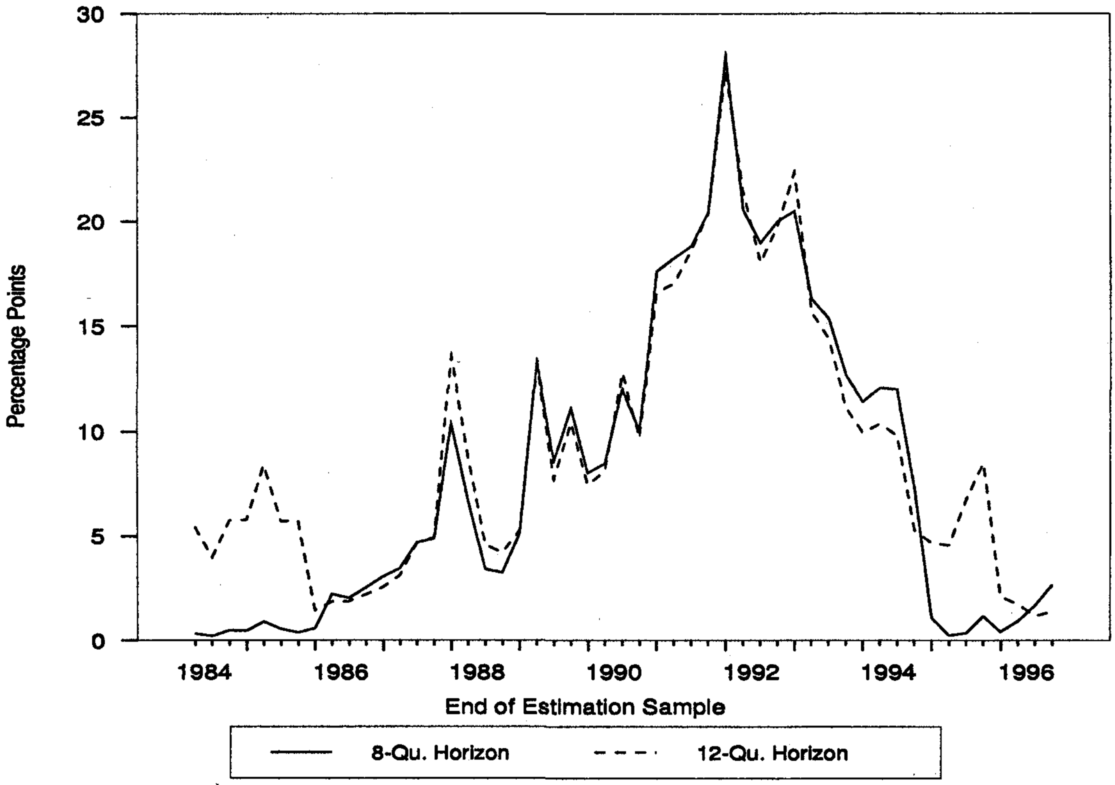
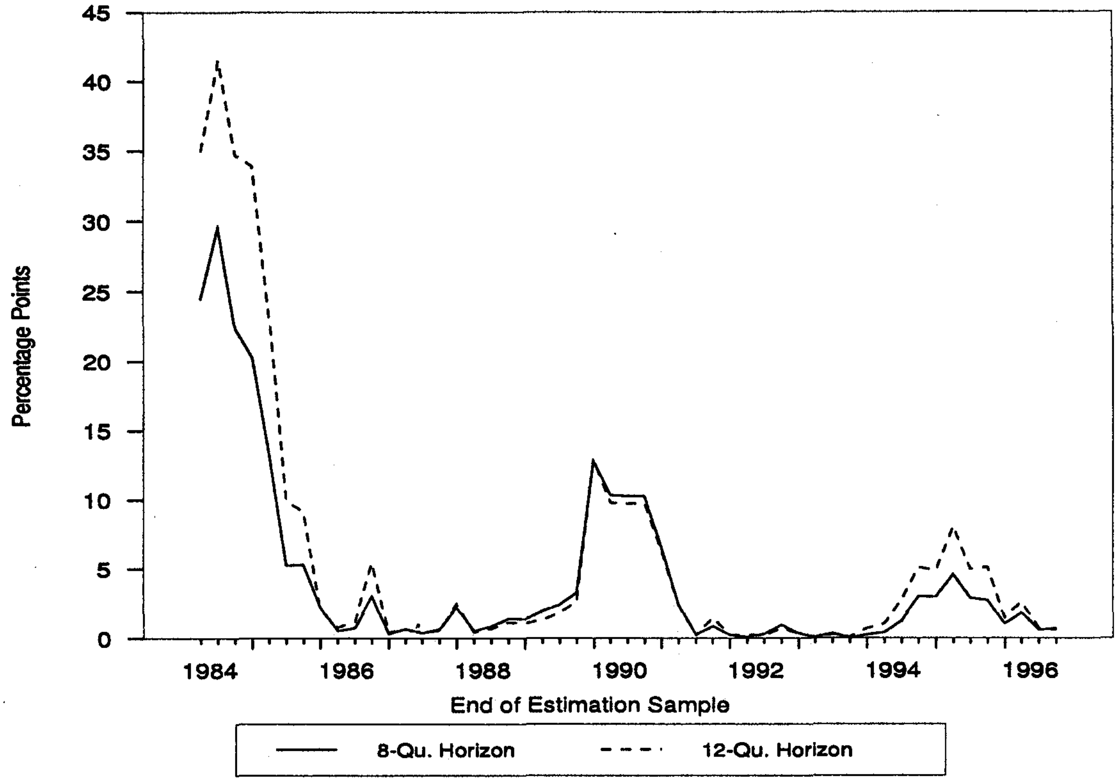


Figure 2

y p e **VAR**

A: Forecast error variance of output explained by exchange rates



B: Forecast error variance of prices explained by exchange rates

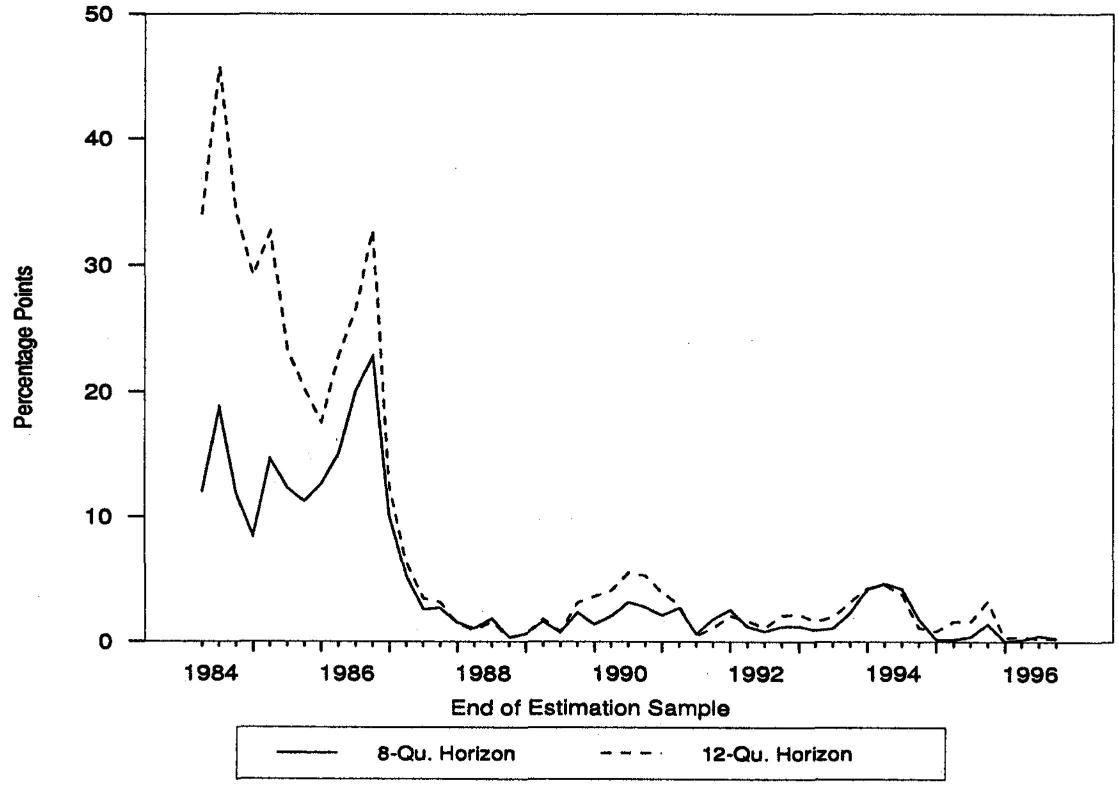


Figure 3

y p m e **VAR**

A: Forecast error variance of output explained by money

B: Forecast error variance of output explained by exchange rates

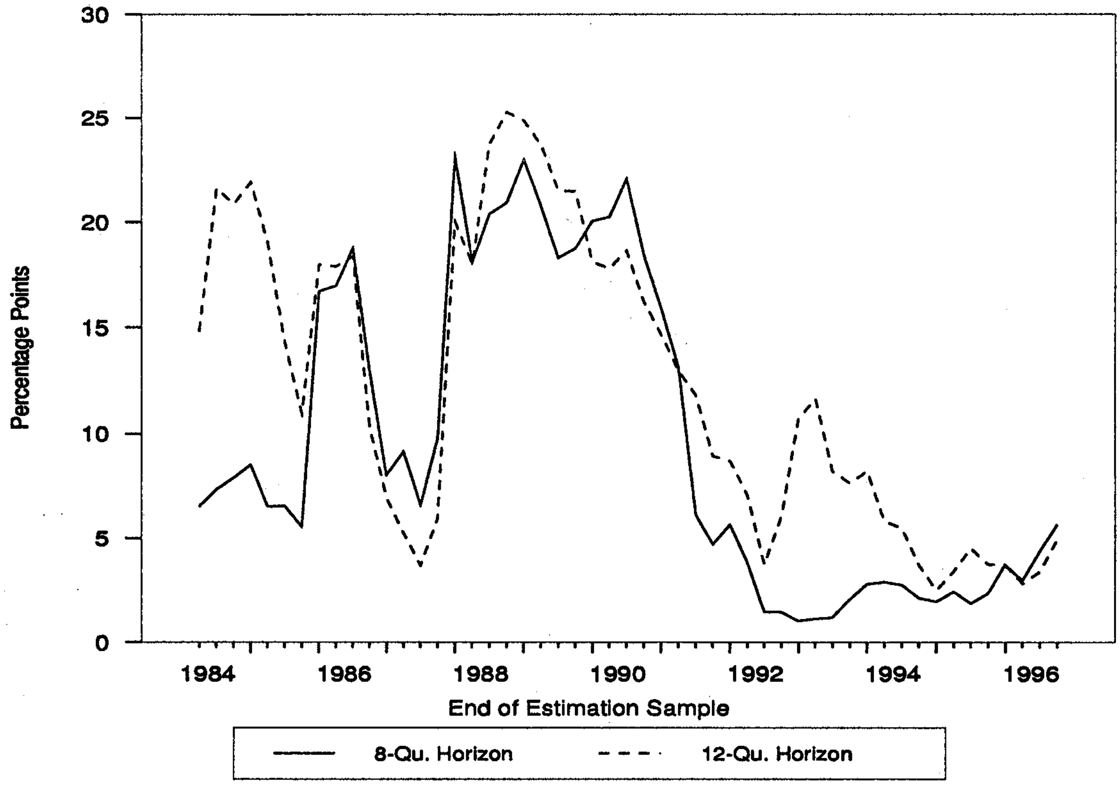
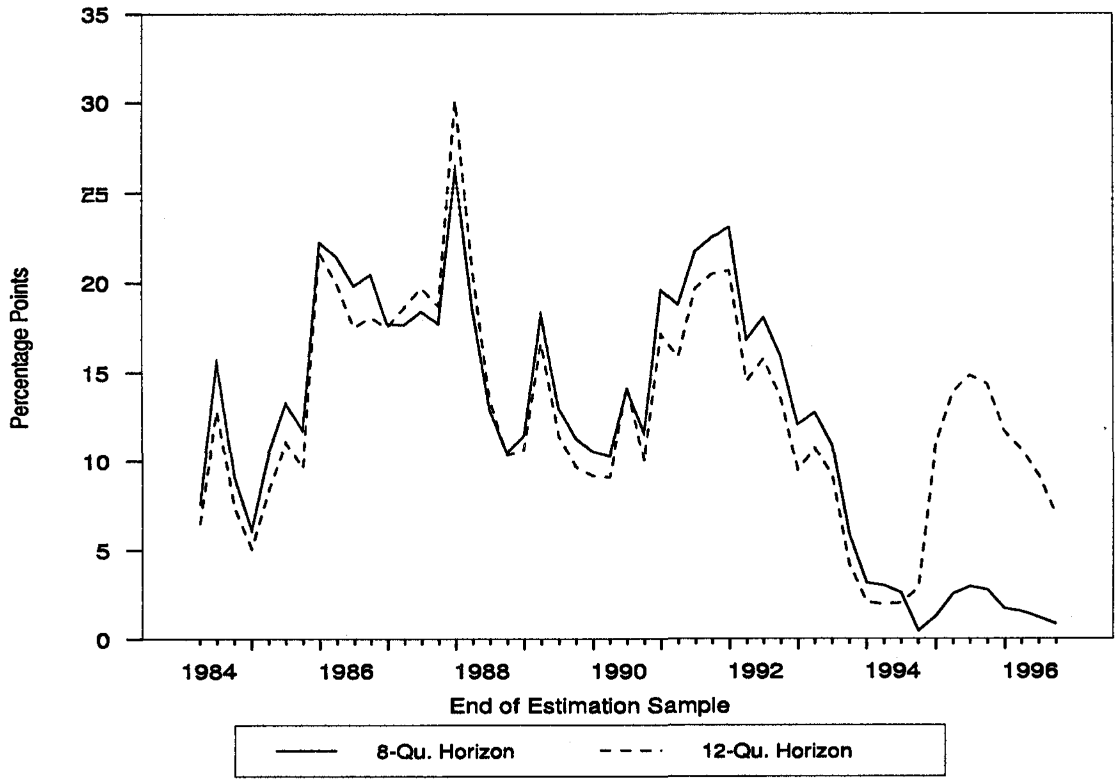


Figure 3 (cont.)

y p e **VAR**

C: Forecast error variance of prices explained by money



D: Forecast error variance of prices explained by exchange rates

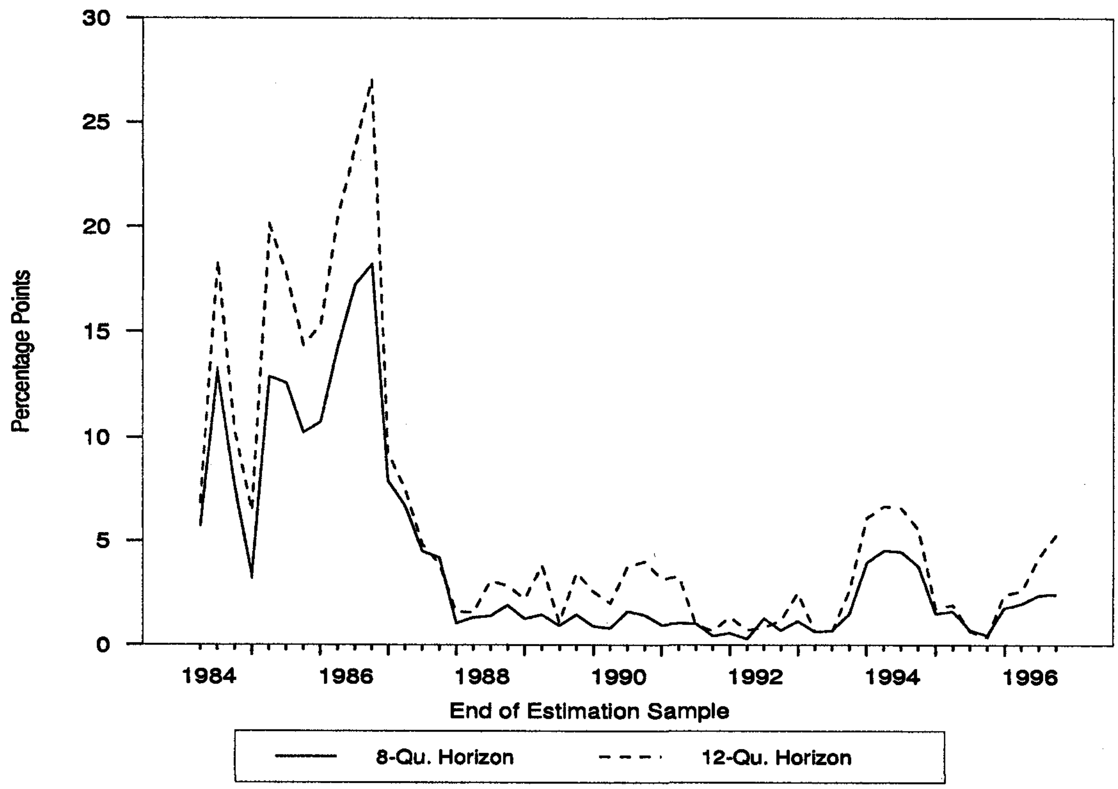
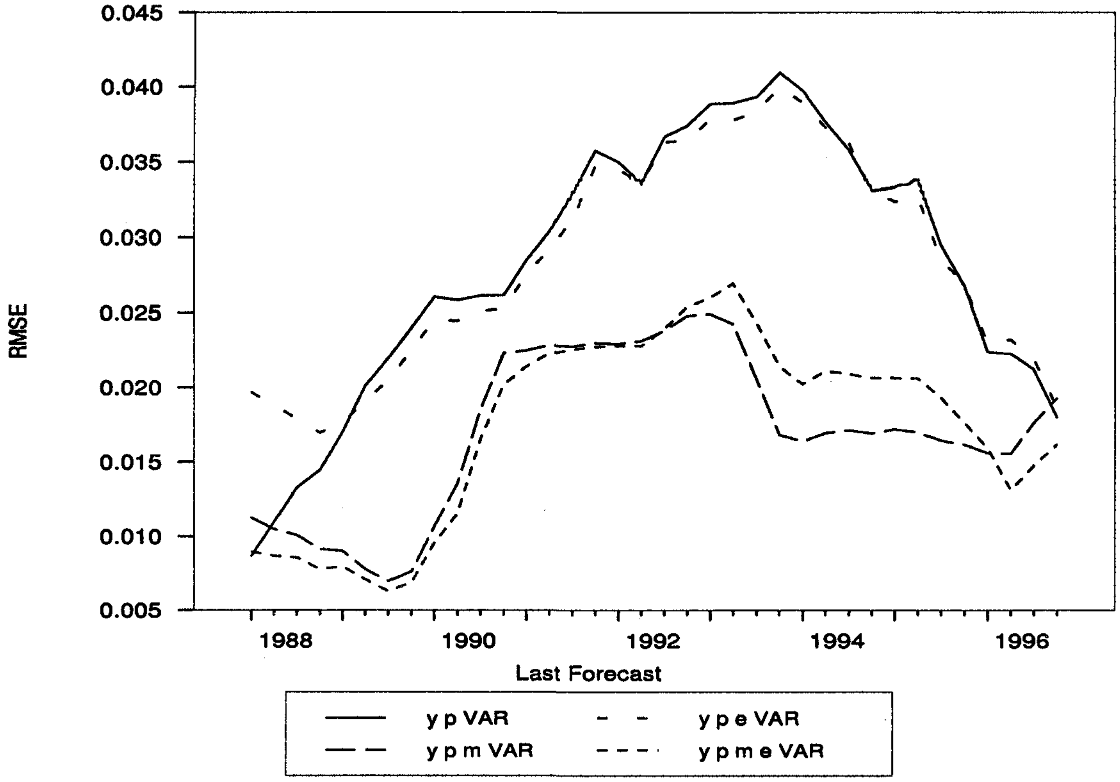


Figure 4

Root mean square error of 4-quarter-ahead forecasts

A: Output



B: Prices

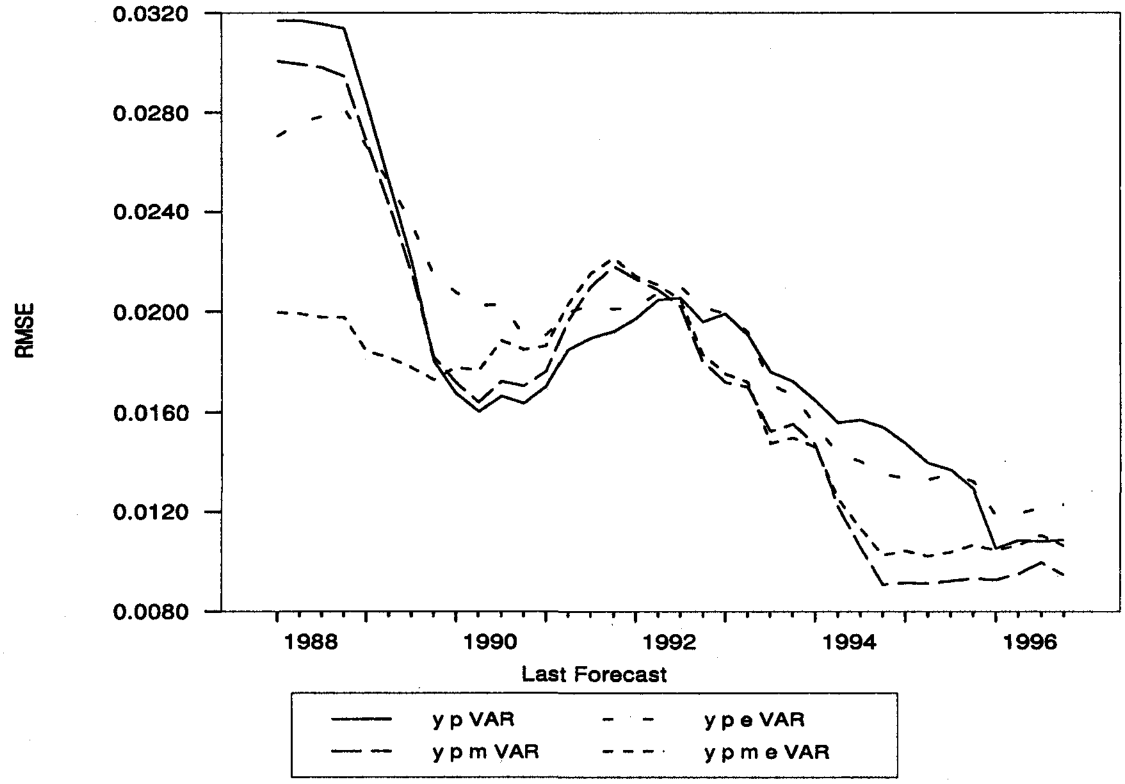
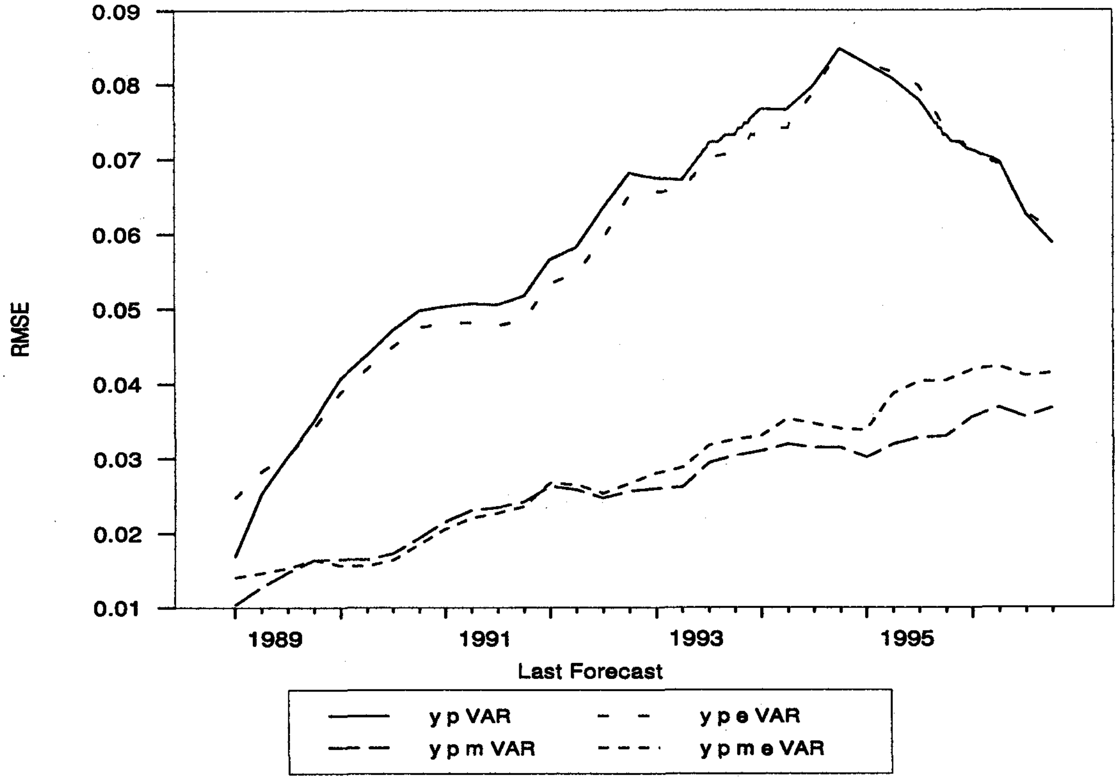


Figure 5

Root mean square error of 8-quarter-ahead forecasts

A: Output



B: Prices

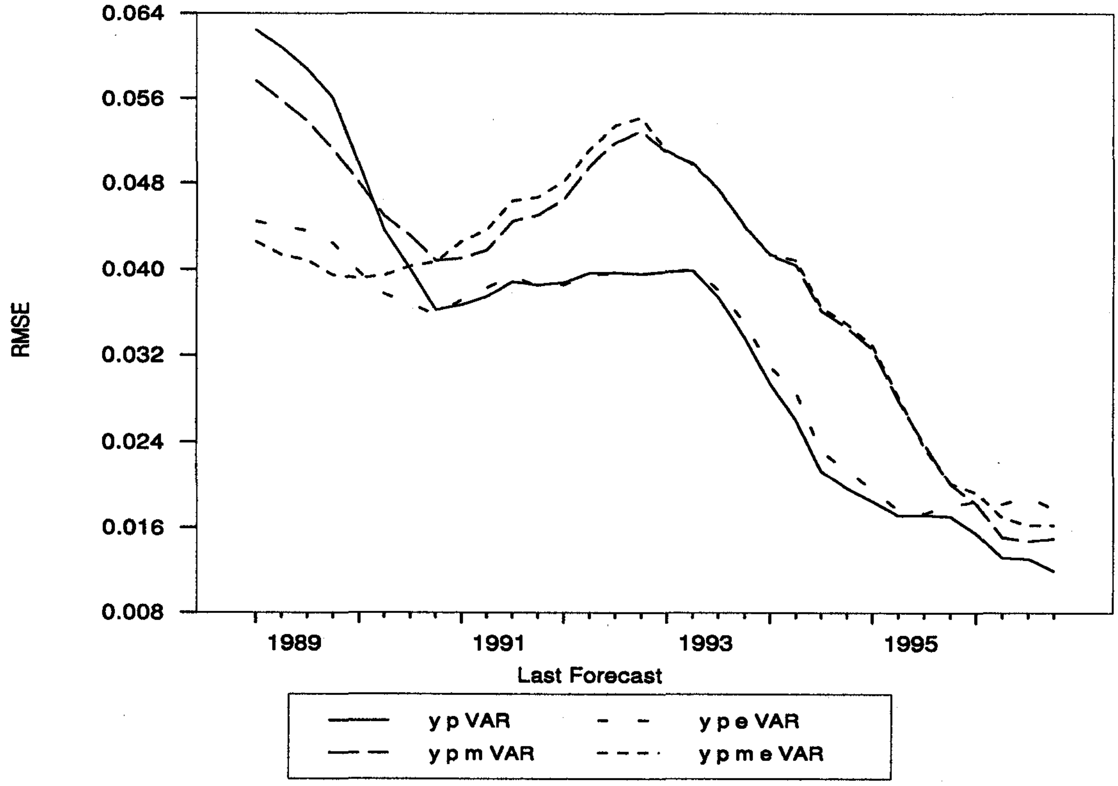
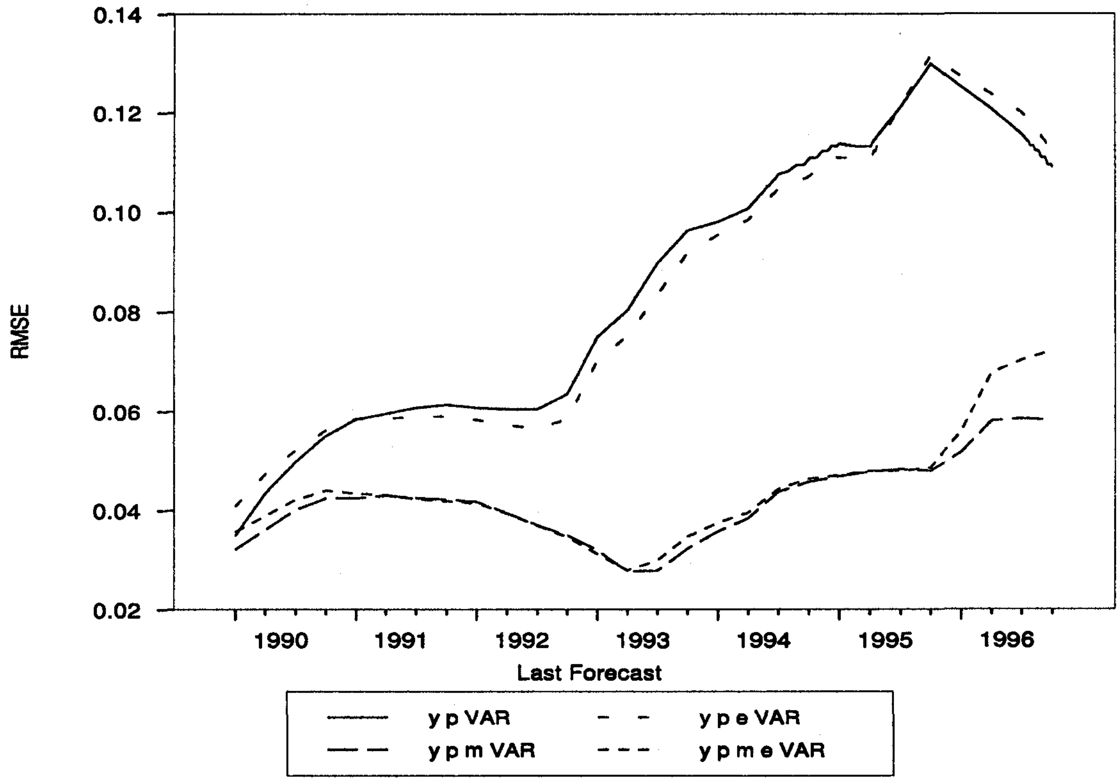


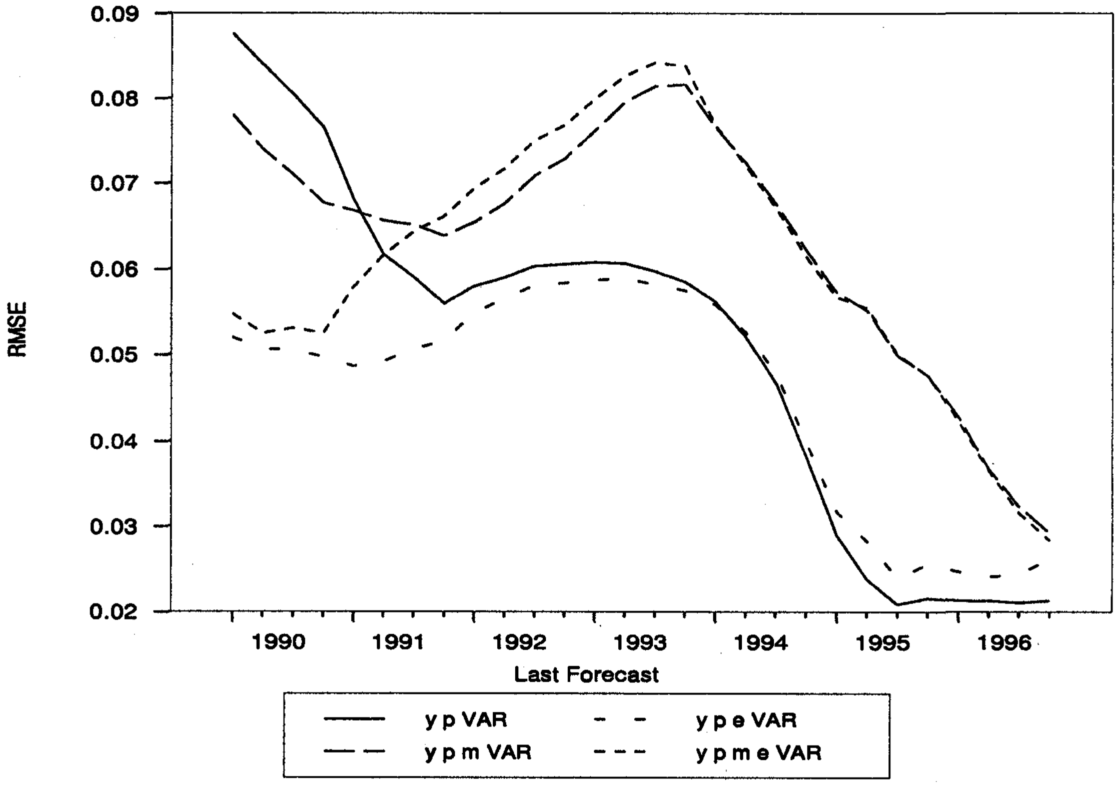
Figure 6

Root mean square error of 12-quarter-ahead forecasts

A: Output



B: Prices



exchange rate index is included in the VAR system. This underlines that money and exchange rates together contain more stable information about prices and output than each of these variables considered alone.

Next, I consider the evolution of the out-of-sample forecasting ability. I compute forecasts for the 4, 8 and 12-quarter horizon as explained in Section 2 based on samples of 40 observations. Then, the root mean square error is computed for 12 consecutive forecast errors. For example, the RMSE reported in 1988:1 refers to the 12 forecast errors from 1985:2 through 1988:1 and the RMSE reported in 1988:2 refers to the 12 forecast errors from 1985:3 through 1988:2 and so on. This is done for all 3 forecast horizons. In order to find out whether the financial variables keep their predictive information content for output and prices, I also include the *y p* VAR in the analysis.

The results are reported in Figures 4 to 6. In general, the RMSE of output becomes bigger, the more recent the data included in the sample, but the RMSE for output of both the *y p* VAR and the *y p e* VAR improves again if data after 1994 are included. Conversely, the RMSE for prices generally declines if the sample is shifted forward. This is true for all 4 different VARs considered. There are two important findings: First, the information content of the financial variables, especially the exchange rate index, for forecasting prices deteriorates over time. The simple *y p* VAR achieves the lowest RMSE at the end of the observed data, compared with the larger systems with the exception of the 4-quarter horizon, where all systems achieve similar RMSEs. Second, for forecasting output, the inclusion of money still improves the forecasts at longer horizons, i.e., the systems including *m* achieve lower RMSEs than those without money. This is less clear for the 4-quarter horizon. These findings confirm that forecasting output has recently become more difficult relative to forecasting prices. Whereas money and exchange rates may still improve output forecasts, they now contain little information about prices at the horizons considered. The out-of-sample results are basically consistent with the in-sample findings. The only discrepancy lies in the different judgements about the information content of the exchange rate index for predicting output.

Conclusions

This study reconsidered the information content of a set of financial variables for forecasting output and prices in Switzerland during the post Bretton Woods era. The analysis covers three parts. First, the in-sample predictive content of the variables is analysed. Second, the out-of-sample forecasting ability is considered. Third, the study asks whether the information content changes over time. In all parts of the paper vectorautoregression methodology is applied, so that the information content of the financial variables is measured as the additional predictive information which is not already extractable from observing the time series of output and prices themselves.

The results show that money contains important information for forecasting output. The information content has recently declined, but forecasts based on systems including money still outperform systems without money. Including the exchange rate index in the forecast system may render the forecast ability more stable over time, but the evidence is not clear-cut. Exchange rates turned out to be helpful for predicting prices. However, the information content of the exchange rate index has deteriorated strongly in recent years, so that the best forecasts for prices are based on a forecasting system including only output and prices.

The results from this exercise lead to three conclusions. 1. Financial variables and asset prices lose information content for predicting output and prices during the 1990s. 2. Forecasting prices gradually becomes easier during the 1990s because more information is contained in the time series of prices itself. This indicates that the inflation process may have changed during the 1990s. In contrast, forecasting output becomes gradually more difficult especially at longer horizons because of the loss of information of money. 3. The information contents of the VAR systems are not robust over time. Rolling regression techniques may help to find out whether one VAR system gradually becomes less attractive than another for forecasting output and prices.

It is important to remember that the information content of the financial variables is defined in a specific statistical manner. The information content of a specific variable is measured as the incremental predictive power over the part of movements of output and prices that is not already forecastable from past values of output, prices and, in general, from the variables placed ahead in the order of orthogonalisation. If monetary policy consists of systematic responses to past fluctuations in output and prices, the information content of money may be small although its impact on output and prices may be large. Furthermore, if money growth is relatively stable, the correlation between money and prices and between money and output can be small even if money has powerful effects. Consequently, knowing that the information content of money is small for prices and declining for output does not mean that the central bank should abandon monetary aggregates as information variables or as intermediate targets. In addition, none of the other financial variables considered delivered better information for forecasting prices and output in a consistent manner. Thus, the study does not favour the use of such variables as indicators for monetary policy in Switzerland and underlines the difficulties the Swiss National Bank would face if it pursued a policy of inflation targeting instead of a policy of monetary targeting.

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