Staff memo

Indicators for short-term fore-casting

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S V E R I G E S   R I K S B A N K

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Staff memos

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Summary

Good short-term forecasting is crucial for assessing economic developments also in the longer term. The Riksbank uses a large number of indicators and various models to forecast variables such as GDP, employment and inflation. At the same time, the availability of new indicators is increasing rapidly. In this staff memo, we examine which indicators improve the short-term forecasts for Swedish GDP growth, employment growth and CPIF inflation. We also refer to earlier evaluations. In our evaluation, we compare “newer” indicators with indicators that have been part of the economic assessment for a long time, but may not have been formally evaluated. Examples of the first group of indicators are quantitative responses from the Riksbank’s Business Survey, internet data on food prices and card data. Examples of data that have been included in the analysis for a long time are data from the Economic Tendency Survey and the Swedish Public Employment Service. This study also examines whether the indicators can help explain the turbulent economic developments since 2020.

For example, we find that various financial market indicators, such as stock market developments, help to improve the forecasts for GDP and employment. Employment forecasts are also improved when statistics on redundancies are included in the models. Data from the Riksbank’s Business Survey and an index of supply chain disruptions also contribute to better forecasts of CPIF inflation in the short term. In general, the contribution of the indicators to forecast accuracy increases when the turbulent years 2020–2023 are included.

We also find that credit card data is a good indicator in several areas of consumption. New data on food prices from the price monitoring company Matpriskollen can be used to improve forecasts of corresponding prices included in the CPI.

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1 The amount of new data is increasing rapidly

Making good present assessments and short-term forecasts of the macroeconomy is important for forecast accuracy in the longer term, and for making well-informed economic decisions.[2] The importance of a good nowcast was also recognised by Faust and Wright (2013), who concluded that it is very difficult to beat a medium-term inflation forecast that links a good nowcast with long-term inflation expectations.

Forecasts are often based on historical data and modelling. Although the development of new forecasting models is progressing relatively slowly, more is happening in terms of data availability.[3] By analysing new data sources, we can gain a better understanding of economic trends and changes, which can improve forecast accuracy, see for example Stock and Watson (2002a and 2002b), Giannone et al. (2008), Banbura et al. (2011), Andreou et al. (2013) and Laine and Lindblad (2021).[4] This staff memo examines some examples of new information, and whether it can be used to improve short-term forecasts.

Credit card data is an example of data that can be used to improve short-term forecasting. Such information can, for example, provide early signals of changing consumer behaviour, where a reduction in consumption expenditure can be a sign of an upcoming economic downturn. Carlsen and Storgaard (2010) were among the first to use card data in forecasting models, when they utilised Dankort payments to improve the nowcasting of retail sales indices in Denmark. Galbraith and Tkacz (2015) used Canadian debit card transactions to improve forecasts for the Canadian economy. Duarte et al. (2017) use high-frequency ATM data to model current private consumption in Portugal. Using Mixed Data Sampling (MIDAS) models, they find that such data improve forecast accuracy in the short term. Weekly data performs particularly well, while daily data seems to be too volatile. Barnett et al. (2016) first develop an indicator of monetary and credit card services, which is then used in a multivariate state-space model to improve nowcasts of GDP growth in the United States. Aprigliano et al. (2017) use more traditional economic indicators together with payment data in a dynamic factor model to forecast Italian GDP growth. They find that monthly payment data help to improve forecast accuracy in the short term. Examples of traditional economic indicators are electricity consumption, industrial production, inflation, stock market indices and manufacturing indices. Examples of payment data are cheques, credit transfers and card payments.

Online prices are a significant and growing source of data, which can improve forecast accuracy. They are accessed through data scraping or web scraping. Traditional data sources are often updated on a monthly or quarterly basis. Online prices, on the other hand, are updated daily or even in real time. This makes it possible to capture rapid

[2] Forecasting at shorter horizons is also known as nowcasting.

[3] Some examples where short-term forecasting models are evaluated are Andersson and Löf (2007) and Andersson and den Reijer (2015).

[4] During and after the pandemic, the Riksbank has started to explore data sources other than official statistics more actively, see Ewertzh et al. (2020).

changes in economic conditions, which can prove valuable when making short-term forecasts. Lünnemann and Wintr (2011) wrote one of the first papers in this area. They collected more than five million price quotes from price comparison websites for France, Italy, Germany, the United Kingdom and the United States, and they found that prices change more frequently for certain product categories in the European countries. Cavallo and Rigobon (2016) used web scraping to collect online prices from the largest retailers in Argentina, Brazil, Chile, Colombia and Venezuela, and they found that it improved short-term inflation forecasts. Over the years, the Riksbank has collected and processed price information, which is published online, in order to obtain a better current picture of price movements in certain areas. Examples include the prices of fruit and vegetables and air travel.[5]

Financial market information is another example of continuously and rapidly updated data that can provide an indication of where economic developments are heading. These include stock prices, bond yields, interest rates and exchange rates. Such indicators have long been used in the Riksbank's nowcasting, and are thus not an example of a new type of data. But they are included in this staff memo, so that they can be evaluated more formally. Some of this data, such as stock indices, are forward-looking as they are largely based on market expectations. This makes a forecast evaluation of them particularly interesting.

Survey data have also long been used to inform short-term forecasts. Although this type of data is subjective, it can provide insight into people's perceptions and expectations. This information can help us understand how people may react to different events or changes, which in turn can help us make more accurate predictions, see for example Gayer et al. (2014) and Kurz-Kim (2019). In this staff memo, we investigate whether quantitative responses from the Riksbank's Business Survey can contribute to better short-term forecasts.[6]

In this staff memo, we look at each of the above data categories, and examine how they contribute to increased forecast accuracy for Swedish GDP, employment and inflation in the short term. We then compare the result with the forecast accuracy when using a univariate model. The analysis also compares the forecast accuracy of these "new" indicators with more traditional indicators, such as data from the Economic Tendency Survey, the Purchasing Managers' Index and the Swedish Public Employment Service.

In particular, we find that financial market indicators and some survey data contribute to improved GDP forecasts. Employment forecasts also improve when financial indicators are included, but here, statistics on redundancies are also important. For CPIF inflation, new data from the Riksbank's Business Survey, together with an index of supply chain disruptions, contribute to better short-term forecasts. In general, the contribution of the indicators to forecast accuracy is greater when the volatile period 2020-2023 is included in the analysis. Our results also suggest that credit card data are a

[5] See, for example, Hull et al. (2017).

[6] A summary index of the responses in the Riksbank's Business Survey has been evaluated previously, see Holmer (2023).

good indicator in several areas of consumption, and that online food prices from the price monitoring company Matpriskollen can be used to improve the food price forecast in the CPIF.

2 Method and data

To analyse the forecasting ability of the indicators, this staff memo mainly uses the Bayesian vector autoregressive model (BVAR model):

$$\mathbf{G}(\mathrm{L})(\mathbf{y}_{\mathrm{t}} - \boldsymbol{\mu}) = \boldsymbol{\eta}_{\mathrm{t}} \tag{1}$$

As the equation above indicates, the model is expressed in terms of the deviations of the variables from their steady states, $\boldsymbol{\mu}$. This property was introduced by Villani (2009), and has the advantage that a prior distribution for the steady states of the variables in the system can be used, the nx1 vector $\boldsymbol{\mu}$. This can be particularly useful when forecasting Swedish CPIF inflation, for example, as the Riksbank has an explicitly stated inflation target. This specification has also been shown to produce better forecasts on average than "ordinary" vector autoregressive models, simple comparison models and the National Institute of Economic Research's (NIER) published forecasts, see for example Lindholm et al. (2020).

In model (1):

$$\mathbf{G}(L) = \mathbf{I} - \mathbf{G_1}\mathrm{L} - \cdots - \mathbf{G_1}\mathrm{L}^{\mathrm{m}}$$

a polynomial of time shifts is of order m. In this study, however, the Schwarz information criterion is minimised in the vast majority of cases when $m = 1$, which means that model (1) can be written:

$$(\mathbf{y}_{\mathrm{t}} - \boldsymbol{\mu}) = (\mathbf{y}_{\mathrm{t-1}} - \boldsymbol{\mu}) + \boldsymbol{\eta}_{\mathrm{t}},$$

where $\mathbf{y}_{\mathrm{t}}$ is a *n*x1 vector of stationary variables and $\boldsymbol{\eta}_{\mathrm{t}}$ is a *n*x1 vector of independent and equally distributed error terms with:

$$\mathrm{E}(\boldsymbol{\eta}_{\mathrm{t}}) = \mathbf{0} \text{ och } \mathrm{E}(\boldsymbol{\eta}_{\mathrm{t}}\boldsymbol{\eta}_t') = \boldsymbol{\Sigma}.$$

The priors on the dynamics of the model have been slightly modified compared to the traditional Minnesota prior (see Doan et al., 1984), which is standard when using the steady-state specification (see Villani, 2009).

The prior on $\boldsymbol{\mu}$ is given by $\boldsymbol{\mu} \sim \mathrm{N}(\boldsymbol{\theta}_{\boldsymbol{\mu}}, \boldsymbol{\Omega}_{\boldsymbol{\mu}})$ and specified in detail in Table A1 in Appendix A. The parameters of the model's prior distribution, so-called hyper-parameters, are also in line with what is commonly used in the literature. We set the overall tightness parameter to 0.2, the cross-variable tightness to 0.5 and the lag-decay parameter to 1.

Model 1 is estimated both univariately, i.e. with only one of the three evaluation variables GDP growth, employment growth and CPIF inflation, and bivariately, where one indicator at a time is included (the indicators are listed in Table 2-5 below). This makes it easy to study whether the indicators contribute to improving forecast accuracy. The results are presented in terms of ratios of root mean square error (RMSE) from the bivariate BVAR model to the univariate model:

$$\frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(y_{t+h}-\hat{y}^{bivariat}{}_{t+h|t}\right)^{2}}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(y_{t+h}-\hat{y}^{univariat}{}_{t+h|t}\right)^{2}}}, \tag{2}$$

where T is the number of forecasts made, y is one of the evaluation variables and h is the forecast horizon. If the ratio in (2) is less than 1 at a given forecast horizon h, it implies that the forecast accuracy of the bivariate model is better than that of the univariate model and vice versa. We will also test whether the forecast accuracy is statistically significantly better using the Diebold and Mariano test (1995), see Appendix B for details.

Regardless of the length of the historical data available, we have chosen to focus on evaluating the forecasts for the period 2013Q1 to 2023Q2 for all indicators.[7] This is done with a progressively longer estimation period. The first forecast generated is based on data up to 2012Q4, and then forecasts are made from 2013Q1 onwards.[8] In the next step, the model is estimated on data up to 2013Q1, and forecasts are calculated from Q2, etc.

For reference, the numerator of equation (2) also uses RMSE from a couple of comparison models. In this study, we use a so-called naive forecast as a comparison model for which the forecast h points in time ahead is always equal to the latest actual outcome. We also use the mean of the last 12 outcomes as a comparison forecast, and finally we use two BVAR models with 7 and 11 variables each. See footnote to Table A1 in Appendix A for details on the variables included in BVAR (7) and BVAR (11).

Table 1 below provides information on the variables to be forecast, and Tables 2 to 5 provide information on the indicators that will be assessed in this staff memo.[9]

Table 1: Evaluation variables[10]

Variable	Time period	Transformation
GDP growth	1996Q1-2023Q2	YoY
CPIF inflation	1996Q1-2023Q2	YoY
Employment growth	1996Q1-2023Q2	YoY
HUKO	2020m1-2023m12	YoY
Food prices in the CPIF	2021m1-2023m12	MoM

Note. YoY indicates annual percentage change and MoM monthly percentage change. Employment applies to the 15-74 age group. HUKO is the Household Consumption Indicator at current prices observed on a monthly basis.
Source: Statistics Sweden.

[7] Section 3.1 also evaluates models for the period 2013Q1-2019Q4, see Tables 9-11.

[8] We focus on the short term, which means one to two quarters ahead. However, the appendix provides results for forecasts further ahead, up to eight quarters ahead.

[9] In the different categories of indicators, we have chosen to evaluate those that are most highly correlated with the evaluation variable.

[10] Household consumption expenditure (HCE), including five subgroups of HCE, and food prices are evaluated in partial models in Section 3.2. An alternative measure of inflation, und24f, has also been evaluated (see footnote 17).

Table 2: Data from the Riksbank's Business Survey

Variable	Time period	Transformation
Indicator of Economic Activity[11]	2008Q2-2023Q2	SU
Economic situation (now)	2008Q2-2023Q2	SU
Employment (3m)	2008Q2-2023Q2	SU
Investment plans (6m)	2008Q2-2023Q2	SU
Price changes (12m)	2008Q2-2023Q2	SU
Wage drift (12m)	2008Q2-2023Q2	SU
Profitability (now)	2008Q2-2023Q2	SU

Note. SU indicates standardised units, where the variables have been transformed so that the mean is equal to 100 and the standard deviation is equal to 10. The suffix (now) refers to a nowcast, while the suffixes (Xm) refer to expectations at the different horizons of 3, 6 or 12 months.
Source: Sveriges Riksbank.

Table 3: Data from the National Institute of Economic Research's (NIER) Economic Tendency Survey[12]

Variable	Time period	Transformation
Confidence indicator (ind)	1996Q2-2023Q2	SU
Confidence indicator (tot)	1996Q2-2023Q2	SU
Recruitment plans	2001Q1-2023Q2	SU
Unemployment (households)	1996Q1-2023Q2	SU
Price plans (trade)	2003Q2-2023Q2	SU
Price plans (services)	2003Q3-2023Q2	SU
Labour hoarding indicator (LHind)	2010Q3-2023Q2	SU

Note. SU indicates standardised units. Confidence indicator refers to the NIER's confidence indicators where the suffix (ind) refers to the manufacturing industry. These include both questions about the current situation and plans (expectations). Recruitment plans refer to the expectations for the next three months (next quarter). Unemployment (households) refers to the question, which is asked to households: *During the past 12 months, has your risk of becoming unemployed increased, decreased or remained unchanged?*. The labour hoarding indicator (LHind) refers to an indicator of the proportion of firms that have a larger workforce than they need, in other words, the proportion of firms that are labour hoarding.
Source: National Institute of Economic Research.

[11] This is an aggregation of 11 questions in the Riksbank's Business Survey, see Holmer (2023).

[12] Many of the indicators from the NIER's Economic Tendency Survey have long been included in the Riksbank's short-term models, but they have not been evaluated in this way before. The contribution of the economic tendency survey data is also interesting to use as a comparison with the other indicators in this study.

Table 4: Financial data

Variable	Time period	Transformation
OMX30	1996Q1-2023Q2	YoY
OMX all share	1996Q1-2023Q2	YoY
OMX mid cap	1996Q1-2023Q2	YoY
OMX small cap	1996Q1-2023Q2	YoY
EPU_Sweden	1996Q1-2023Q2	SU
EPU_Global	1996Q1-2023Q2	SU
Spread (10y 2y)	1996Q1-2023Q2	Per cent
Spread (1y 3m)	1996Q1-2023Q2	Per cent
Volatility (VIX CBOE)	1996Q1-2023Q2	Index
Volatility (VIX futures)	2004Q2-2023Q2	Index
Financial conditions (FCI RB)	1996Q1-2023Q2	SU

Note. For transformations, see note to Tables 1 and 2. OMX30 is an index of the 30 most frequently traded shares on the Stockholm stock exchange. OMX all share is an index of all shares on the Stockholm Stock Exchange and OMX mid cap and OMX small cap are indices of the shares on the mid cap and small cap lists. EPU_Sweden and EPU_Global refer to so-called economic policy uncertainty indices, see Baker et al. (2016). Spread (10y 2y) and Spread (1y 3m) refer to the difference between the yields on a 2-year and a 10-year government bond and between a 1-year and a 3-month government bond. VIX CBOE and VIX futures are two measures of expected stock market volatility, see Chicago Board Options Exchange. The FCI RB is a summary index of financial conditions calculated by the Riksbank.

Sources: Nasdaq OMX Nordic, Sveriges Riksbank and the Chicago Board Options Exchange.

Table 5: Other data[13]

Variable	Time period	Transformation
Supply chain pressure (GSCPI)	1997Q4-2023Q2	SU
PMI (ind)	1996Q1-2023Q2	SU
Redundancies	1996Q1-2023Q2	Number of persons
Card data	2020m1-2023m12	YoY
Food prices_MPK	2021m1-2023m12	MoM

Note. For transformations, see note to Tables 1 and 2. Supply chain pressure (GSCPI) refers to a summary index measuring the degree of supply chain disruption, see Federal Reserve Bank of New York. The PMI (ind) from Swedbank refers to the Purchasing Managers Index (PMI) and is a business cycle indicator for the Swedish economy for the manufacturing industry. Card data refers to card transaction data from Swedbank and Food_Prices_MPK refers to food prices from price monitoring company Matpriskollen.

Sources: Federal Reserve Bank of New York, National Institute of Economic Research, Statistics Sweden, Swedbank, Swedish Public Employment Service and Matpriskollen.

[13] Card data and Food_prices_MPK are evaluated in partial models in Section 3.2. Card data and HUKO are divided into five subcategories.

3 Results

This section presents the results. First, forecasts for the longer period, to Q2 2023, are evaluated. Section 3.1 evaluates forecasts excluding the period 2020-2023.

Tables 6-8 below show the one- and two-quarter root mean square errors for the bivariate models, relative to the root mean square errors for the univariate models calculated using the BVAR model (1). Appendix C shows actual RMSEs for each model and also for longer forecast horizons.

The results for GDP growth show that comparative models perform worse than the univariate model, in this particular period and with these specifications. For a naive forecast, which means that the forecast is always equal to the last known outcome, and for a mean forecast, the precision is 10-20 per cent worse than for a univariate forecast at the forecast horizons of 1 and 2 quarters, see Table 6. Furthermore, the univariate model performs about as well in the short run as the “heavier” multivariate models BVAR(7) and BVAR(11).[14] Quantitative data from the Riksbank’s Business Survey make, on average, a weakly positive contribution to forecast accuracy when added to a univariate model.[15] This result is broadly in line with results where data from the Economic Tendency Survey are included. As already mentioned, financial market data often have a clear forward-looking element which, in some cases, help to improve the accuracy of GDP growth forecasts. This is especially true for equity indices (OMX30, OMX all share and OMX mid cap), which all have a significantly lower RMSE compared to the univariate model. This is according to Diebold and Mariano's test. Uncertainty indices (VIX CBOE and VIX futures), financial conditions (FCI RB) and PMI also contribute to up to about 10 per cent better GDP forecasts, but here the difference from the univariate forecast is not statistically significantly different from zero.

[14] The univariate model is specified in the same way as the VAR models, but only includes the forecast variable itself.

[15] Holmer (2023) obtains similar results with the new Indicator of Economic Activity, which is based on data from the Riksbank’s Business Survey. The results also suggest that the indicator improves forecast accuracy more clearly if pandemic data are included in the evaluation period (compare with the results in Section 3.1). The measurable quantitative responses can be followed over time. In addition, the respondent's qualitative descriptions of the economic situation are summarised in the Business Survey.

Table 6. Relative forecast accuracy for GDP growth

Evaluation period 2013Q1 to 2023Q2

		1 quarter	2 quarters
Models	***Univariate***	***1.00***	***1.00***
	Naive forecast	*1.07*	*1.14*
	Mean_12	*1.17*	*1.12*
	BVAR(7)	*1.02*	*1.00*
	BVAR(11)	*1.02*	*0.99*
Business Survey (RB)	Indicator of Economic Activity	0.97	0.94
	Economic situation (now)	1.00	0.99
	Employment (3m)	0.98	0.98
	Investment plans (6m)	0.93	0.94
Economic Tendency Survey (NIER)	Confidence indicator (ind)	0.99	0.98
	Confidence indicator (tot)	0.96	0.93
Financial data	OMX30	0,87*	0,82*
	OMX all share	0,89*	0.88
	OMX mid cap	0.92	0,85*
	OMX small cap	0.92	0.93
	EPU_Sweden	0.99	0.97
	EPU_Global	1.02	1.03
	Spread (10y 2y)	0.98	0.99
	Spread (1y 3m)	1.02	1.00
	VIX CBOE	0.95	0.89
	VIX futures	0.95	0.90
	FCI RB	0.98	0.93
Other data	PMI (ind)	0.93	0.93
	Supply chain pressure (GSCPI)	1.06	1.09
	Redundancies	0.94	0.97

Note. Ratios of RMSE relative to univariate forecast. A value below 1 means that the model with indicators has a lower RMSE than the univariate model without indicators. *, ** and *** means that the model with indicators has significantly higher forecast accuracy than a univariate model at the 10, 5 and 1 per cent significance level, according to Diebold and Mariano's (1995) test. Italicised rows show comparative models. Mean_12 refers to a running mean value over the last 12 observations. Due to data availability, the estimation periods differ for the different indicators, see Tables 1-5 above. However, in Table 6 the relative forecast accuracy (RMSE for bivariate model/RMSE for univariate model) is calculated for the same estimation period.

The relative forecast accuracy for employment growth is shown in Table 7. With the exception of the mean forecast, the comparative models perform roughly in line with the univariate model. Adding the business survey data helps to improve the forecast accuracy slightly. The same applies if equity indices are included in the models. This is particularly the case for the OMX mid cap and OMX small cap stock indices, where the difference from the univariate forecast is significantly different from zero (for OMX small cap). Uncertainty indices (VIX CBOE and VIX futures) and financial conditions (FCI RB) contribute to about 10 per cent lower RMSEs over two quarters. Recruitment plans according to the NIER’s Economic Tendency Survey contribute to a marginally better precision of the forecasts, while households' expectations of the risk of their own unemployment weaken the forecasts. As in the case of GDP growth, the supply chain index (GSCPI) contributes to a slightly lower forecast accuracy. Statistics on redundancies contribute to more than 10 per cent better forecast accuracy one quarter ahead, and here the difference compared with the univariate forecast is statistically significant. Forecast accuracy is also better at longer horizons, see Table C2 in Appendix C.

Table 7. Relative forecast accuracy for employment growth

Evaluation period 2013Q1 to 2023Q2

		1 quarter	2 quarters
Models	***Univariate***	***1.00***	***1.00***
	Naive forecast	*1.03*	*1.06*
	Mean_12	*1.69*	*1.41*
	BVAR(7)	*1.01*	*1.02*
	BVAR(11)	*0.99*	*0.99*
Business Survey (RB)	Indicator of Economic Activity	0.96	0.96
	Economic situation (now)	0.96	0.98
	Employment (3m)	0.95	0.97
	Investment plans (6m)	0.95	0.96
Economic Tendency Survey (NIER)	Recruitment plans	0.95	0.97
	Unemployment (households)	1.02	1.04
	LHind	1.01	0.98
Financial data	OMX30	0.96	0.96
	OMX all share	0.95	0.92
	OMX mid cap	0.92	0.87
	OMX small cap	0.90	0,83*
	EPU_Sweden	0.99	0.98
	EPU_Global	1.01	1.03
	Spread (10y 2y)	0.97	0.97
	Spread (1y 3m)	0.99	0.98
	VIX CBOE	0.99	0.94
	VIX futures	0.98	0.93
	FCI RB	0.97	0.89
Other data	Supply chain pressure (GSCPI)	1.03	1.07
	Redundancies	0,86*	0.88

Note. See note in Table 6.

The univariate model's current forecasts for CPIF inflation are on average worse than a naive forecast, about as good as alternative BVAR models and significantly better than mean value forecasts, see Table 8. It is interesting to note that the naive forecast has performed well during the high inflation of recent years, compared to the alternatives examined here.[16] The main reason is that the model forecasts underestimated to a greater extent the rapid rise in inflation in 2022.

Indicators from the business survey contribute to slightly lower RMSE at one and two quarters. Unlike the forecasts for GDP and employment growth, financial market data do not improve forecast accuracy that much. The possible exception is financial conditions (FCI RB), which contribute to a decrease in the RMSE of around 5 per cent. Of the NIER's indicators, price plans in the services sector appear to be the most promising. Statistics on redundancies and the supply chain pressure indicator lower the RMSE by up to 10 per cent when included in the univariate model. However, none of the changes in the forecast accuracy for CPIF inflation are statistically significant.

[16] The naive forecast improves significantly compared to the univariate forecast when the period 2020-2023 is included in the assessment, compare Table 8 and Table 11.

Table 8. Relative forecast accuracy for CPIF inflation[17]

Evaluation period 2013Q1 to 2023Q2

		1 quarter	2 quarters
Models	***Univariate***	***1.00***	***1.00***
	Naive forecast	*0.91*	*0.86*
	Mean_12	*2.52*	*1.52*
	BVAR(7)	*1.02*	*0.99*
	BVAR(11)	*1.00*	*0.99*
Business Survey (RB)	Indicator of Economic Activity	0.95	0.95
	Wage drift (12m)	0.94	0.94
	Profitability (now)	0.97	0.98
	Price changes (12m)	0.94	0.95
Economic Tendency Survey (NIER)	Price plans (trade)	0.98	0.99
	Price plans (services)	0.96	0.96
Financial data	OMX30	1.01	0.99
	OMX all share	1.01	1.00
	OMX mid cap	0.97	0.97
	OMX small cap	0.96	0.96
	EPU_Sweden	0.98	0.99
	EPU_Global	0.99	1.02
	Spread (10y 2y)	0.96	0.98
	Spread (1y 3m)	0.98	0.99
	VIX CBOE	1.02	1.10
	VIX futures	1.00	1.06
	FCI RB	0.95	0.95
Other data	Supply chain pressure (GSCPI)	0.93	0.92
	Redundancies	0.96	0.95

Note. See note in Table 6.

3.1 Sensitivity analysis

In this study we have chosen to: Firstly, evaluate the forecasts for the period, which include the turbulent period of pandemic and war in recent years. Second, make the evaluation variables and indicators available up to and including the same quarter of the evaluation.[18] In this subsection, we change these conditions to see how the results change.

Excluding 2020–2023 from the evaluation period, there are signs that the contributions from the indicators decrease. The indicators have thus been particularly valuable in recent times. If the period 2020-2023 is excluded for GDP growth, for example, the relative forecast accuracy deteriorates for virtually all indicators and horizons, compare Table 9 and Table 6. The same is also true for forecasts at longer horizons, compare for example Tables C1 and C4 in Appendix C.

The value of the indicators in improving accuracy since 2020 can be explained by the fact that the indicators move faster and more in response to various shocks. For example, during the pandemic outbreak, several indicators already moved in the first

[17] The contributions of the indicators are on average slightly larger if the inflation measure und24 is used instead. This measure implies that price groups that have fluctuated relatively much over the past 24 months will have a lower weight and vice versa. But even with this measure, the forecast accuracy is not significantly higher for any indicator than for a univariate model.

[18] This is not a real-time evaluation. In other words, we do not use different versions of forecast variables and indicators.

quarter of 2020, while GDP and employment data largely fell only in the second quarter. Inflation only began to rise clearly in 2022Q1, which can largely be explained by supply chain disruptions, see Table 8 and Löf and Stockhammar (2024).

Table 9. Relative forecast accuracy for GDP growth
Evaluation period 2013Q1 to 2019Q4

		1 quarter	2 quarters
Models	***Univariate***	***1.00***	***1.00***
	Naive forecast	*1.06*	*1.11*
	Mean_12	*1.93*	*1.44*
	BVAR(7)	*1.24*	*1.32*
	BVAR(11)	*1.16*	*1.22*
Business Survey (RB)	Indicator of Economic Activity	0.98	1.01
	Economic situation (now)	1.07	1.08
	Employment (3m)	0.99	1.01
	Investment plans (6m)	0.99	0.95
Economic Tendency Survey (NIER)	Confidence indicator (ind)	1.01	1.00
	Confidence indicator (tot)	0.97	0.96
Financial data	OMX30	0,88*	0,84*
	OMX all share	0,90*	0,81*
	OMX mid cap	1.00	0.98
	OMX small cap	0.99	1.01
	EPU_Sweden	1.03	1.02
	EPU_Global	1.16	1.27
	Spread (10y 2y)	1.02	1.04
	Spread (1y 3m)	1.07	1.11
	VIX CBOE	0.98	0.92
	VIX futures	0.97	0.93
	FCI RB	0.98	0.95
Other data	PMI (ind)	0.95	0.95
	Supply chain pressure (GSCPI)	1.02	1.00
	Redundancies	0.98	0.97

Note. See note in Table 6.

The results for GDP growth show that comparative models perform worse than the univariate model, in this particular period and with these specifications. Data from the Riksbank's Business Survey and from the National Institute of Economic Research's Economic Tendency Survey contribute neither positively nor negatively on average to the forecast accuracy. As with the results when also assessing the 2020-2023 period, financial market data contribute in some cases to a clear increase in the forecast accuracy for GDP growth. This is especially true for stock indices (OMX30 and OMX all share), which have a significantly lower RMSE compared to the univariate model. Uncertainty indices (VIX CBOE and VIX futures) and financial conditions (FCI RB) also contribute to slightly better GDP forecasts.

The relative forecast accuracy of employment growth is shown in Table 10. In this respect, the forecast accuracy of the comparative models is quite similar to the results of the univariate model. If data from the business survey are added, they contribute only marginally to improving forecast accuracy. The same applies to the OMX30 and OMX all share indices. Similarly to the use of 2020-2023 data, the forecast accuracy increases when small cap stock indices are included and the difference from the univariate forecast is significantly different from zero two quarters ahead. Uncertainty indices (VIX futures) and financial conditions (FCI RB) contribute to about 5 per cent lower RMSE two quarters ahead. Recruitment plans according to the NIER's Economic

Tendency Survey contribute to marginally better forecast accuracy, while households' expectations of the risk of their own unemployment weaken the forecasts. Statistics on redundancies contribute to a 5 per cent improvement in forecast accuracy, while the supply chain pressure index (GSCPI) marginally worsens forecast accuracy.

Table 10. Relative forecast accuracy for employment growth
Evaluation period 2013Q1 to 2019Q4

		1 quarter	2 quarters
Models	***Univariate***	***1.00***	***1.00***
	Naive forecast	*1.00*	*0.94*
	Mean_12	*1.30*	*1.12*
	BVAR(7)	*1.00*	*0.97*
	BVAR(11)	*1.00*	*0.98*
Business Survey (RB)	Indicator of Economic Activity	0.98	1.03
	Economic situation (now)	1.02	1.00
	Employment (3m)	0.98	1.04
	Investment plans (6m)	1.01	0.99
Economic Tendency Survey (NIER)	Recruitment plans	0.96	1.00
	Unemployment (households)	1.08	1.32
	LHind	1.08	1.01
Financial data	OMX30	0.99	1.00
	OMX all share	0.99	0.95
	OMX mid cap	0.94	0,83*
	OMX small cap	0.94	0,82*
	EPU_Sweden	1.02	1.04
	EPU_Global	1.08	1.20
	Spread (10y 2y)	1.02	1.04
	Spread (1y 3m)	1.04	1.04
	VIX CBOE	1.00	0.98
	VIX futures	0.99	0.94
	FCI RB	0.99	0.95
Other data	Supply chain pressure (GSCPI)	1.01	1.05
	Redundancies	0.95	0.95

Note. See note in Table 6.

For CPIF inflation, the forecasts from a univariate model are on average slightly better than simple comparative models, see Table 11. The new indicator of economic activity and the question on wage drift in one year (Wage_drift_12m) contribute to a few per cent lower RMSE, one and two quarters ahead. Other indicators from the business survey and financial market data contribute neither positively nor negatively to the forecast accuracy. The possible exception is financial conditions (FCI RB), which contribute to a decrease in the RMSE of around 5 per cent. Price plans in the services sector appear to be the most promising of the NIER indicators. The GSCPI contributes, if anything, to marginally worse forecast accuracy for CPIF inflation. This is not the case when the period 2020-2023 is included in the evaluation. However, none of the changes in forecast accuracy are statistically significantly different from zero. This also applies to the longer evaluation period.

Table 11. Relative forecast accuracy for CPIF inflation
Evaluation period 2013Q1 to 2019Q4

		1 quarter	2 quarters
Models	***Univariate***	***1.00***	***1.00***
	Naive forecast	*0.98*	*0.99*
	Mean_12	*1.98*	*1.74*
	BVAR(7)	*1.03*	*1.11*
	BVAR(11)	*1.02*	*1.08*
Business Survey (RB)	Indicator of Economic Activity	0.96	0.99
	Wage drift (12m)	0.97	0.96
	Profitability (now)	1.00	1.05
	Price changes (12m)	1.00	1.01
Economic Tendency Survey (NIER)	Price plans (trade)	1.05	1.13
	Price plans (services)	0.97	0.97
Financial data	OMX30	0.99	1.02
	OMX all share	0.98	1.02
	OMX mid cap	0.97	0.98
	OMX small cap	0.96	0.97
	EPU_Sweden	1.01	1.06
	EPU_Global	1.00	1.08
	Spread (10y 2y)	0.99	1.01
	Spread (1y 3m)	0.98	1.01
	VIX CBOE	0.99	1.02
	VIX futures	0.98	0.99
	FCI RB	0.94	0.96
Other data	Supply chain pressure (GSCPI)	1.04	1.09
	Redundancies	0.98	0.99

Note. See note in Table 6. As for the evaluation period 2013Q1 to 2019Q4, there is no significant change in the results if und24 is used as a measure of inflation, see footnote 17.

Forecast accuracy increases slightly if indicators are shifted

In the analysis above, we have chosen to leave the evaluation variables and indicators available until the same quarter. In practice, however, it may be the case that the indicators are available a few months later than the evaluation variable. In some cases, the indicator is even available a full quarter ahead of the evaluation variable. For example, the number of redundancies may be available for quarter 2, while employment growth is only available for quarter 1 of a specific year. Taking this into account should lead to better forecasts for the evaluation variables. Such specifications are examined below, where all indicators are available a full quarter ahead of GDP, employment and the CPIF. The evaluation period here is 2013Q1 to 2019Q4. The conclusions are the same if one instead evaluates the projections to 2023Q2.

For GDP growth, the RMSE relative to the univariate projection improves slightly if the indicators are available for one more quarter. But the difference is rather small with the exception of a couple of financial indicators two quarters ahead, compare Table 12 and Table 9.

Table 12. Relative forecast accuracy for GDP growth
The indicators are available one quarter longer than for GDP. Evaluation period 2013Q1 to 2019Q4.

		1 quarter	2 quarters
Models	***Univariate***	***1.00***	***1.00***
	Naive forecast	*1.06*	*1.11*
	Mean_12	*1.93*	*1.44*
	BVAR(11)	*1.16*	*1.22*
Business Survey (RB)	Indicator of Economic Activity	0.95	0.95
	Investment plans (6m)	1.02	0.98
Economic Tendency Survey (NIER)	Confidence indicator (tot)	0.97	0.94
Financial data	OMX30	0,90*	0,75**
	OMX all share	0.95	0,82*
	OMX small cap	1.01	0.90
	VIX CBOE	0.99	0.93
	FCI RB	0.99	0.95
Other data	Supply chain pressure (GSCPI)	1.04	1.02
	Redundancies	0.97	0.93

Note. See note in Table 6.

For employment growth, it matters even less if the indicators are available for another quarter. The difference is very small, compare Table 10 and Table 13.

Table 13. Relative forecast accuracy for employment growth
The indicators are available one quarter longer than for employment. Evaluation period 2013Q1 to 2019Q4.

		1 quarter	2 quarters
Models	***Univariate***	***1.00***	***1.00***
	Naive forecast	*1.00*	*0.94*
	Mean_12	*1.30*	*1.12*
	BVAR(11)	*1.00*	*0.98*
Business Survey (RB)	Indicator of Economic Activity	0.98	0.91
	Investment plans (6m)	0.97	1.03
Economic Tendency Survey (NIER)	Recruitment plans	0.99	1.02
Financial data	OMX30	0.99	0.96
	OMX all share	1.00	0.97
	OMX small cap	0.97	0.85
	VIX CBOE	1.00	0.97
	FCI RB	1.00	1.03
Other data	Supply chain pressure (GSCPI)	1.01	1.03
	Redundancies	0.99	0.96

Note. See note in Table 6.

As with GDP and employment growth, the relative forecasting precision for CPIF inflation does not improve significantly if the indicators are allowed to be available for one more quarter, compare Table 11 and Table 14.

Table 14. Relative forecast accuracy for CPIF inflation.
The indicators are available one quarter longer than for the CPIF. Evaluation period 2013Q1 to 2019Q4

		1 quarter	2 quarters
Models	***Univariate***	***1.00***	***1.00***
	Naive forecast	*0.98*	*0.99*
	Mean_12	*1.98*	*1.74*
	BVAR(11)	*1.02*	*1.08*
Business Survey (RB)	Indicator of Economic Activity	0.95	0.95
	Wage_drift_12m	0.96	0.98
Economic Tendency Survey (NIER)	Price plans (services)	0.95	0.97
Financial data	OMX30	0.99	1.03
	OMX all share	0.97	1.00
	OMX small cap	0.96	0.96
	VIX CBOE	0.98	1.02
	FCI RB	0.96	0.98
Other data	Supply chain pressure (GSCPI)	0.97	0.99
	Redundancies	0.97	1.00

Note. See note in Table 6.

The root mean square errors for the forecast horizons of 1 to 8 quarters for all three evaluation variables, where the indicators are assumed to be available one quarter later than the evaluation variables, are shown in Tables C7-C9 in Appendix C.

3.2 Private consumption and food price indicators

Private consumption

Swedbank's card transaction data for the period August 2020 to January 2024 are analysed here.[19] These statistics are compared with data from Statistics Sweden's monthly indicator of household consumption expenditure (HUKO) for a number of consumption areas, measured in current prices. We ask whether short-term data are useful as an early indicator, and more specifically whether they can help to make HUKO forecasts one month before HUKO is published.[20]

Total expenditure and five smaller areas of consumption are analysed here (see Table 15 below). Data from Swedbank are available as daily data and published weekly. Data are expressed as annual percentage changes from 8 January 2020. HUKO is available further back in time and is published on a monthly basis by Statistics Sweden. The analysis below uses a monthly average of the short series, so that it can be evaluated against HUKO. The annual percentage change in total consumption expenditure according to HICP and card data is shown in Figure 1 below. Figures 2 to 6 in Appendix D show the correlation between HUKO and card data for the other consumption areas. It can already be seen here that short-term data for several types of consumption

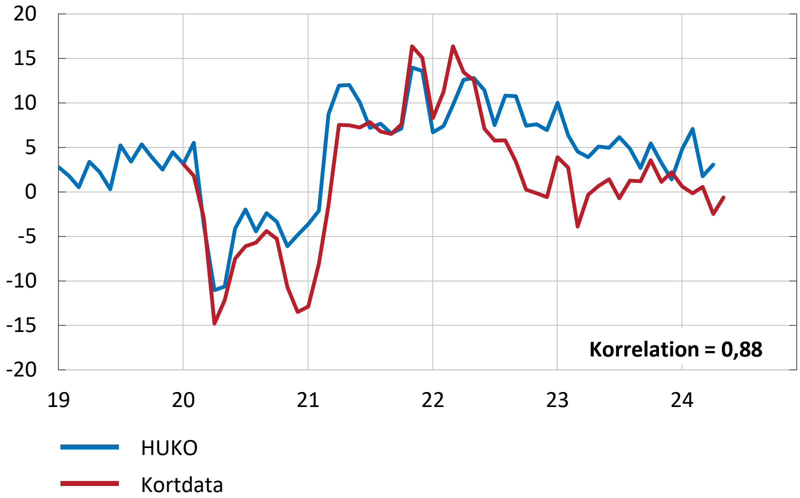
[19] The card statistics capture the transactions made with payment cards via Swedbank Pay's payment solution, both in store and online.

[20] Short-term data for a full month are published at least one month before HUKO is published for the corresponding month.

correlate relatively well with the consumption indicators.[21] In cases where the correlation is lower, it may be a matter of individual observations going in different directions, which contribute to a lower correlation.

Diagram 1. Total consumption according to HUKO and card data

Annual percentage change



Note. Correlation indicates the correlation between HUKO and the card data over the period.

Sources: Statistics Sweden and Swedbank.

Table 15. Consumption data from Statistics Sweden and Swedbank[22]

Total expenditure
Restaurants, cafés, hotels and other accommodation services
Food and drink
Recreation and culture, goods and services
Clothing and shoes
Furniture, furnishings, household equipment and consumables

Sources: Statistics Sweden and Swedbank (Macrobond)

We model annual percentage changes and use AR-like models instead of VAR models, because the evaluation period is so short. Forecasts from models that include card data are compared with forecasts from models without card data. We therefore ask whether short-term data leads to better forecasting ability, for one or more of the consumption areas analysed.[23] We further assume that card data are available one month further ahead than HUKO.[24] The models are first estimated on data for the period January 2020 to June 2020. HUKO is then available until June, while short-term data are assumed to be available until July. Forecasts are generated from both specifications. In the next step, HUKO data are used until July, while card data are available

[21] See estimated correlation coefficients in the charts.

[22] HUKO is the Household Consumption Indicator, current prices and the column labelled Card data refers to Swedbank's payment statistics, 7-day moving average.

[23] The informational value may appear to be relatively limited in this case, when the forecasting ability for several smaller consumption areas is analysed. However, such information was very important during the pandemic when trying to get a grip on the current situation.

[24] Transaction data are often available two months ahead of HUKO.

until August. The models are re-estimated, and forecasts are generated one month ahead and so on. The following specifications are used:

$$\Delta_{12} C_t^{HUKO} = \alpha_0 + \beta_0 \Delta_{12} C_{t-1}^{HUKO} + \beta_q \Delta_{12} C_t^{KORT} + \varepsilon_t \quad (3)$$

$$\Delta_{12} C_t^{HUKO} = \beta_0 + \beta_1 \Delta_{12} C_{t-1}^{HUKO} + \mu_t \text{ , } (4)$$

where C_t^{HUKO} indicates consumption according to HUKO and C_t^{KORT} Swedbank card data. Table 16 summarises the forecast results for the period August 2020 to January 2024 (43 months). As above, relative root mean square errors are calculated according to equation (2), with values above one indicating that model 4 (without card data) produces smaller forecast errors, while numbers below one mean that model 3 (with card data) has made more accurate forecasts. In most cases, short-term data seem to improve forecasting ability. However, there is one exception: recreation and culture, goods and services. The evaluation period is very short and the period is special, as it includes the pandemic. The results also change quite a lot as more observations are gradually added to the analysis. Nevertheless, the results so far suggest that card data can be a good indicator in several areas of consumption.

Table 16. Relative RMSE (model 3/model 4)

	Relative RMSE
Total expenditure	0.96
Restaurants, cafés, hotels and other accommodation services	0.46
Food and drink	0.74
Recreation and culture, goods and services	1.06
Clothing and shoes	0.98
Furniture, furnishings, household equipment and consumables	0.71

Sources: Statistics Sweden and Swedbank (Macrobond).

Food prices

Since spring 2023, the Riksbank has subscribed to data from the price monitoring company, Matpriskollen.[25] The Riksbank updates data weekly for 20 product groups, and the dataset is available from January 2021. Data from Matpriskollen are used as an indicator in the Riksbank's short-term models for various aggregates of food prices, and these models are evaluated here.[26] The sub-aggregate being modelled is food excluding alcohol and tobacco, which has a weight of 13.3 per cent in the CPIF (denoted p^{199} below). The information from the 20 product groups is summarised in two factors, which are derived using principal component analysis (pc1 and pc2 below). Data on vegetable prices from Matpriskollen are also included as an explanatory variable (*vegetables*). The regression models monthly percentage changes. It uses the information from Matpriskollen together with two dummy variables for the months of March and July and a moving average term (*MA*). The model that includes data from

[25] An independent application that collects prices from different chains and stores, https://Matpriskollen.se/.

[26] For a more detailed discussion of this statistic, see Tysklind (2024).

Matpriskollen is compared with a model that looks the same but does not include data from Matpriskollen. The two specifications are thus as follows:

$$\Delta_1 p_t^{199} = \alpha_0 + \beta MPK_t^{pc1,pc2+gronsaker} + \gamma D_t^{mars,juli} + \delta MA(1) + \varepsilon_t \qquad (5)$$

$$\Delta_1 p_t^{199} = \alpha_0 + \gamma D_t^{mars,juli} + \delta MA(1) + \varepsilon_t \qquad (6)$$

Table 17 shows the relative RMSEs, evaluated for the period July 2022 to December 2023 (18 months). The value of 0.62 indicates that data from Matpriskollen contribute to an average of about 40 per cent lower RMSE, compared to an alternative model. However, the estimation and evaluation periods are very short, so the results should be interpreted with caution.

Table 17. Relative RMSE (model 5/model 6)

	Relative RMSE
CPI199 (food excluding alcohol and tobacco)	0.62

Sources: Statistics Sweden and Matpriskollen.

4 Conclusions

In this staff memo, we have examined the extent to which various indicators improve the forecast accuracy of Swedish GDP growth, employment growth and CPIF inflation in the short term. Some of the data we are studying are new, while other data have been part of the nowcast for some time but have not been formally evaluated. We find that, in some cases, financial market data contribute to increased forecast accuracy for all three variables. This should be explained by the fact that these data are largely forward-looking. For example, some Swedish stock indices (OMX) contribute to significantly improved forecast accuracy for GDP and employment growth. The Financial Conditions Index (FCI) contributes to more than 5 per cent more accurate forecasts on average for all three variables.

Among the time series from the Riksbank's Business Survey, the Indicator of Economic Activity and the question on wage drift in 12 months' time contribute to slightly lower RMSEs for inflation one and two quarters ahead. This is similar to the forecasting ability of the NIER's indicators, which contribute to slightly better forecast accuracy for GDP growth (the confidence indicator), employment (recruitment plans) and inflation (price plans in the services sector). The same is true for the manufacturing PMI. The forecast accuracy for employment improves significantly when statistics on redundancies are included in the model. Other measures such as the labour hoarding indicator, global supply chain pressure index and simple comparative models generally lead to lower forecast accuracy. The exception is the supply chain pressure index, which proved to be valuable in improving the nowcasts for CPIF inflation. If the indicators are assumed to be published one quarter later than the evaluation variable, the forecast accuracy improves slightly. What makes a big difference to the results is the inclusion of data for the volatile period 2020–2023 in the forecast evaluation. Indicators have generally been more important in the turbulent period of recent years than in more normal times.

In the case of card data, the conclusions depend on the data transformation used. In this staff memo, only results using annual percentage changes are presented. The evaluation period is short, and the period analysed is specific. The results also change gradually, as more observations are added to the analysis. However, the results up to December 2023 suggest that card data are a good indicator for several areas of consumption. Although the time series are short, the results with new food price data from the price monitoring company Matpriskollen also suggest that they can help to improve the forecasts of food prices measured by Statistics Sweden.

Suggestions for future analysis to potentially improve the forecast accuracy of some key macroeconomic aggregates include improving existing situation models and developing new ones. This can be done, for example, with new versions of dynamic factor models or other new methods, where different frequencies of data can be mixed, see for example Algaba et al. (2023). The analysis can also be extended by including new types of data, which are currently not available to the Riksbank. One example is using mobile data to forecast GDP growth and employment. Mobile data can be, for example, internet activity, mobile banking and GPS tracking. For example, Matsumura et al. (2021) show that mobile data can improve nowcasts for production in the services sector. Furthermore, online searches and text analysis can be used to try to improve short-term forecasts of GDP, employment and inflation. Aswin et al. (2021) show for example that newspaper articles from mainstream newspapers can improve current forecasts of GDP growth in the euro area, as newspapers contain up-to-date economic signals. This is particularly true early in the quarter, when there is a lack of other indicators. The Riksbank is involved in the field of machine learning, which is an exciting and rapidly developing field. Such methods are discussed, for example, in Lenza et al. (2023).

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Appendix A - Priors at steady state

Table A1. Prior interval for steady states in the BVAR model in equation (1)[27]

Variable	Abbreviation	Prior interval
GDP abroad		(1; 2.5)
Inflation abroad		(1; 3)
Policy rates abroad		(2.5; 4)
Unemployment		(6.5; 8)
Wages		(3; 4.5)
CPIF excl. energy		(1; 3)
Policy rate		(2.5; 4)
Real exchange rate		(120; 135)
GDP		(1; 2.5)
Employment		(0; 0.5)
CPIF inflation		(1; 3)
Indicator of Economic Activity[28]	Indicator of Economic Activity	(-1; 1)
Economic situation, now	Economic situation (now)	(90; 110)
Employment, 3 months	Employment (3m)	(90; 110)
Investment plans, 6 months	Investment plans (6m)	(90; 110)
Price changes, 12 months	Prisförändring_12m	(90; 110)
Wage drift, 12 months	Wage_drift_12m	(90; 110)
Profitability, now	Profitability (now)	(90; 110)
Confidence indicator, manufacturing industry	Confidence indicator (ind)	(90; 110)
Confidence indicator, total	Confidence indicator (tot)	(90; 110)
PMI manufacturing	PMI (ind)	(50; 60)
Recruitment plans	Recruitment plans	(-10; 10)
Households' expectations of unemployment	Unemployment (households)	(-10; 10)
Price plans, retail	Price plans (trade)	(-10; 10)
Price plans, services sector	Price plans (tj)n	(-10; 10)
OMX30 index	OMX30	(0; 10)
OMX all share, index	OMX all share	(0; 10)
OMX mid cap, index	OMX mid cap	(0; 10)
OMX small cap, index	OMX small cap	(0; 10)
Economic policy uncertainty (EPU), Sweden	EPU_Sweden	(90; 110)
Economic policy uncertainty (EPU), Global	EPU_Global	(90; 110)
Spread 10 years - 2 years	Spread (10y 2y)	(0.5; 1.5)
Spread 1 year – 3 months	Spread (1y 3m)	(0; 1)
Volatility index (VIX)	VIX CBOE	(10; 30)
VIX futures	VIX futures	(10; 30)
Financial Condition Index (FCI)	FCI RB	(-0.5; 0.5)
Global supply chain pressure index	GSCPI	(-0.5; 0.5)
The winterisation indicator	LHind	(0; 10))
Redundancies	Redundancies	(10,000; 20,000)

[27] 95 per cent probability interval for steady state. All these priors are assumed to be normally distributed. The variables are defined in Section 2. The first 11 variables are included in "BVAR(11)" which is used as a comparison model in cases where a long history is available. The external variables are trade weighted. The comparative model "BVAR(7)" includes the same variables as in BVAR(11) except for international interest rate, wages, unemployment and the CPIF excluding energy.

[28] Is an aggregation of 11 questions in the Riksbank's Business Survey, see Holmer (2023).

Appendix B - Diebold and Mariano (1995) test for equal forecast accuracy

Let d_t be the difference between the squared forecast error (SFE) of the univariate forecast U and the bivariate forecast B at time t, that is:

$$d_t = KPF_{U,t} - KPF_{B,t} \ .$$

We test the hypothesis $H_0 : E(d_t) = 0$ (equal forecast accuracy) against, for example, $H_1 : E(d_t) > 0$, the bivariate model makes better forecasts than the univariate one, using the Diebold and Mariano test statistics:

$$DM = \frac{\bar{d}}{\sqrt{\hat{f}/n}} \ ,$$

where $\bar{d}$ is the mean of the differences, $\hat{f}$ is the estimated variance of the mean and n is the number of observations. If the null hypothesis is true, the DM statistic asymptotically follows a standard normal distribution.

Appendix C - Root mean square errors

Table C1. RMSE for GDP growth

Evaluation period: 2013Q1-2023Q2

Quarter	1	2	3	4	5	6	7	8
Univariate	*2.54*	*2.79*	*3.18*	*3.62*	*3.41*	*3.40*	*3.21*	*3.20*
BVAR(7)	*2.60*	*2.79*	*3.15*	*3.62*	*3.44*	*3.42*	*3.26*	*3.24*
BVAR(11)	*2.59*	*2.78*	*3.13*	*3.62*	*3.48*	*3.43*	*3.32*	*3.29*
Naive forecast	*2.73*	*3.19*	*3.88*	*4.65*	*4.56*	*4.70*	*4.25*	*4.30*
Mean_12	*2.99*	*3.12*	*3.20*	*3.22*	*3.15*	*3.10*	*3.06*	*3.08*
Indicator of Economic Activity	2.47	2.64	3.01	3.43	3.29	3.36	3.22	3.21
Economic situation (now)	2.55	2.77	3.13	3.57	3.38	3.36	3.19	3.19
Employment (3m)	2.49	2.75	3.11	3.54	3.36	3.34	3.18	3.18
Investment plans (6m)	2.37	2.64	2.97	3.35	3.26	3.20	3.10	3.15
OMX30	2.22	2.30	2.72	3.01	2.90	3.15	3.10	3.25
OMX all share	2.27	2.46	2.75	3.13	3.03	2.92	3.00	2.96
OMX mid cap	2.33	2.38	2.75	3.03	2.87	2.83	2.84	2.85
OMX small cap	2.35	2.61	2.76	3.17	3.06	2.98	3.02	2.99
EPU_Sweden	2.52	2.72	3.13	3.57	3.38	3.39	3.21	3.20
EPU_Global	2.60	2.87	3.32	3.82	3.64	3.66	3.42	3.42
Spread (10y 2y)	2.50	2.77	3.17	3.62	3.42	3.41	3.23	3.21
Spread (1y 3m)	2.59	2.79	3.15	3.62	3.44	3.42	3.26	3.24
VIX CBOE	2.42	2.48	2.75	3.12	2.99	3.09	2.90	2.89
VIX futures	2.41	2.51	2.80	3.17	3.04	3.11	2.94	2.94
FCI RB	2.49	2.60	2.77	3.11	3.04	3.35	3.23	3.14
Confidence indicator (tot)	2.44	2.60	2.93	3.29	3.15	3.38	3.22	3.13
Confidence indicator (ind)	2.52	2.74	3.10	3.53	3.35	3.33	3.17	3.18
PMI (ind)	2.37	2.61	2.96	3.46	3.29	3.28	3.13	3.15
GSCPI	2.69	3.05	3.48	4.13	3.83	3.83	3.49	3.47
Redundancies	2.40	2.72	3.08	3.53	3.39	3.37	3.19	3.20

Note. See note in Table 6. Green and red numbers indicate that the forecast accuracy is more than 0.1 percentage points better and worse, respectively, than the univariate forecast. Black figures indicate that the forecast accuracy is approximately the same (within univariate forecast +/- 0.1 percentage points).
Source: Own calculations.

Table C2. RMSE for employment growth

Evaluation period: 2013Q1-2023Q2

Quarter	1	2	3	4	5	6	7	8
Univariate	*0.88*	*1.14*	*1.36*	*1.62*	*1.70*	*1.80*	*1.86*	*1.92*
BVAR(7)	*0.89*	*1.17*	*1.37*	*1.63*	*1.71*	*1.81*	*1.87*	*1.93*
BVAR(11)	*0.88*	*1.13*	*1.35*	*1.61*	*1.67*	*1.77*	*1.82*	*1.86*
Naive forecast	*0.91*	*1.20*	*1.45*	*1.77*	*1.91*	*2.06*	*2.20*	*2.32*
Mean_12	*1.49*	*1.60*	*1.69*	*1.75*	*1.79*	*1.80*	*1.79*	*1.77*
Indicator of Economic Activity	0.85	1.10	1.29	1.52	1.65	1.75	1.81	1.87
Economic situation (now)	0.85	1.12	1.30	1.53	1.64	1.73	1.78	1.84
Employment (3m)	0.84	1.10	1.29	1.53	1.65	1.74	1.80	1.86
Investment plans (6m)	0.84	1.09	1.29	1.51	1.63	1.71	1.76	1.82
OMX30	0.85	1.10	1.28	1.52	1.62	1.68	1.76	1.81
OMX all share	0.84	1.05	1.27	1.50	1.60	1.65	1.72	1.76
OMX mid cap	0.81	0.96	1.23	1.46	1.52	1.55	1.63	1.68
OMX small cap	0.80	0.95	1.18	1.41	1.51	1.56	1.64	1.69
EPU_Sweden	0.87	1.11	1.34	1.59	1.69	1.79	1.85	1.90
EPU_Global	0.89	1.17	1.40	1.69	1.80	1.93	2.03	2.12
Spread (10y 2y)	0.86	1.10	1.33	1.57	1.64	1.73	1.79	1.83
Spread (1y 3m)	0.87	1.11	1.34	1.59	1.67	1.76	1.81	1.85
VIX CBOE	0.88	1.17	1.39	1.63	1.76	1.83	1.88	1.91
VIX futures	0.87	1.14	1.34	1.59	1.71	1.77	1.83	1.87
FCI RB	0.85	1.05	1.28	1.52	1.62	1.68	1.76	1.81
Recruitment plans	0.84	1.10	1.29	1.52	1.65	1.75	1.81	1.87
Unemployment (households)	0.90	1.19	1.40	1.68	1.78	1.91	2.00	2.08
LHind	0.89	1.12	1.33	1.59	1.67	1.76	1.82	1.87
GSCPI	0.91	1.22	1.44	1.74	1.86	1.96	2.03	2.09
Redundancies	0.76	1.00	1.22	1.52	1.70	1.76	1.83	1.89

Note. See notes in Table 6 and C1.
Source: Own calculations.

Table C3. RMSE for CPIF inflation

Evaluation period: 2013Q1-2023Q2

Quarter	1	2	3	4	5	6	7	8
Univariate	*0.89*	*1.62*	*2.06*	*2.35*	*2.62*	*2.82*	*2.92*	*2.99*
BVAR(7)	*0.90*	*1.60*	*2.05*	*2.34*	*2.60*	*2.79*	*2.88*	*2.95*
BVAR(11)	*0.89*	*1.61*	*2.04*	*2.33*	*2.58*	*2.76*	*2.84*	*2.90*
Naive forecast	*0.81*	*1.39*	*1.84*	*2.23*	*2.56*	*2.88*	*3.10*	*3.27*
Mean_12	*2.24*	*2.46*	*2.64*	*2.78*	*2.87*	*2.93*	*2.96*	*2.97*
Indicator of Economic Activity	0.84	1.54	1.97	2.26	2.54	2.74	2.85	2.93
Wage drift (12m)	0.84	1.52	1.96	2.24	2.50	2.68	2.80	2.88
Profitability (now)	0.86	1.59	1.99	2.28	2.54	2.73	2.82	2.89
Price changes (12m)	0.84	1.54	1.96	2.25	2.51	2.70	2.79	2.89
OMX30	0.89	1.61	2.07	2.36	2.64	2.84	2.94	3.02
OMX all share	0.90	1.62	2.07	2.39	2.66	2.84	2.94	2.99
OMX mid cap	0.86	1.58	2.06	2.34	2.61	2.79	2.88	2.95
OMX small cap	0.85	1.56	2.06	2.34	2.60	2.78	2.87	2.93
EPU_Sweden	0.87	1.60	2.03	2.32	2.60	2.79	2.89	2.97
EPU_Global	0.88	1.64	2.03	2.31	2.58	2.77	2.86	2.93
Spread (10y 2y)	0.85	1.58	1.99	2.27	2.54	2.73	2.83	2.91
Spread (1y 3m)	0.87	1.60	2.00	2.28	2.54	2.72	2.82	2.89
VIX CBOE	0.90	1.78	2.43	2.67	2.61	2.85	2.97	3.05
VIX futures	0.89	1.72	2.32	2.57	2.57	2.80	2.91	2.99
FCI RB	0.84	1.54	2.04	2.33	2.58	2.76	2.84	2.90
Price plans (services)	0.86	1.55	2.00	2.29	2.56	2.75	2.84	2.92
Price plans (trade)	0.87	1.60	2.03	2.32	2.59	2.78	2.88	2.96
GSCPI	0.84	1.51	1.98	2.35	2.63	2.87	3.00	3.07
Redundancies	0.85	1.53	2.01	2.36	2.61	2.83	2.93	2.99

Note. See notes in Table 6 and C1.
Source: Own calculations.

Table C4. RMSE for GDP growth

Evaluation period 2013Q1–2019Q4

Quarter	1	2	3	4	5	6	7	8
Univariate	*0.76*	*1.05*	*1.29*	*1.45*	*1.46*	*1.39*	*1.35*	*1.34*
Naive forecast	*0.81*	*1.17*	*1.48*	*1.75*	*1.81*	*1.78*	*1.75*	*1.74*
Mean_12	*1.47*	*1.52*	*1.55*	*1.58*	1.55	*1.51*	*1.46*	1.40
BVAR(7)	*0.94*	*1.39*	*1.76*	*2.01*	*2.11*	*2.15*	*2.15*	*2.09*
BVAR(11)	*0.90*	*1.31*	*1.63*	*1.84*	*1.88*	*1.91*	*1.89*	*1.85*
Indicator of Economic Activity	0.74	1.06	1.32	1.40	1.43	1.44	1.37	1.41
Economic situation now	0.81	1.14	1.32	1.46	1.48	1.41	1.34	1.30
Employment (3m)	0.75	1.06	1.31	1.43	1.41	1.39	1.36	1.38
Investment plans (6m)	0.75	1.00	1.17	1.27	1.29	1.30	1.33	1.37
OMX30	0.68	0.90	1.17	1.34	1.44	1.38	1.32	1.34
OMX all share	0.69	0.87	1.11	1.27	1.36	1.35	1.35	1.34
OMX mid cap	0.77	1.05	1.19	1.18	1.10	1.00	0.91	1.13
OMX small cap	0.76	1.09	1.31	1.40	1.36	1.18	1.10	1.17
EPU_Sweden	0.79	1.09	1.32	1.47	1.48	1.42	1.34	1.30
EPU_Global	0.89	1.36	1.73	1.88	1.92	1.80	1.74	1.82
Spread (10y 2y)	0.79	1.12	1.38	1.52	1.41	1.27	1.17	1.14
Spread (1y 3m)	0.83	1.18	1.47	1.64	1.67	1.56	1.50	1.51
FCI RB	0.75	1.02	1.25	1.40	1.39	1.37	1.34	1.33
VIX CBOE	0.76	0.98	1.18	1.32	1.33	1.28	1.24	1.22
VIX futures	0.75	1.00	1.21	1.32	1.34	1.32	1.30	1.31
Confidence indicator (ind)	0.77	1.07	1.30	1.47	1.44	1.36	1.31	1.30
Confidence indicator (tot)	0.75	1.03	1.26	1.39	1.40	1.40	1.38	1.32
PMI (ind)	0.74	1.02	1.24	1.39	1.50	1.47	1.39	1.36
GSCPI	0.79	1.07	1.28	1.40	1.41	1.35	1.28	1.32
Redundancies	0.76	1.04	1.23	1.36	1.37	1.35	1.29	1.31

Note. See notes in Table 6 and C1.
Source: Own calculations.

Table C5. RMSE for employment growth

Evaluation period 2013Q1–2019Q4

Quarter	1	2	3	4	5	6	7	8
Univariate	*0.45*	*0.54*	*0.67*	*0.78*	*0.84*	*0.96*	*0.96*	*1.03*
Naive forecast	*0.45*	*0.51*	*0.61*	*0.74*	*0.74*	*0.89*	*0.88*	*0.92*
Mean_12	*0.58*	*0.60*	*0.63*	*0.65*	*0.67*	*0.70*	*0.70*	*0.72*
BVAR(7)	*0.45*	*0.53*	*0.68*	*0.82*	*0.87*	*0.95*	*0.93*	*0.92*
BVAR(11)	*0.44*	*0.49*	*0.61*	*0.75*	*0.76*	*0.83*	*0.82*	*0.84*
Indicator of Economic Activity	0.44	0.56	0.68	0.81	0.92	1.05	1.06	1.14
Economic situation now	0.46	0.54	0.67	0.81	0.86	0.99	1.00	1.08
Employment (3m)	0.44	0.56	0.69	0.84	0.91	1.05	1.07	1.14
Investment plans (6m)	0.45	0.53	0.64	0.77	0.84	0.97	1.01	1.04
OMX30	0.44	0.50	0.65	0.80	0.91	1.03	1.01	1.08
OMX all share	0.44	0.48	0.59	0.74	0.78	0.94	0.94	1.01
OMX mid cap	0.41	0.42	0.47	0.55	0.60	0.76	0.83	0.90
OMX small cap	0.41	0.41	0.52	0.63	0.70	0.86	0.91	1.01
EPU_Sweden	0.45	0.52	0.64	0.75	0.79	0.92	0.91	0.97
EPU_Global	0.48	0.60	0.78	0.91	0.96	1.10	1.04	1.10
Spread (10y 2y)	0.45	0.52	0.62	0.73	0.78	0.90	0.94	0.94
Spread (1y 3m)	0.46	0.52	0.63	0.76	0.81	0.95	0.96	1.04
FCI RB	0.43	0.44	0.57	0.70	0.73	0.84	0.85	0.94
VIX CBOE	0.43	0.47	0.61	0.72	0.75	0.89	0.86	0.95
VIX futures	0.43	0.46	0.57	0.68	0.71	0.82	0.84	0.88
Recruitment plans	0.43	0.50	0.63	0.73	0.81	0.90	0.89	0.93
Unemployment (households)	0.48	0.66	0.86	1.08	1.23	1.34	1.41	1.43
LHind	0.49	0.54	0.68	0.82	0.89	1.00	0.99	1.06
GSCPI	0.45	0.52	0.63	0.76	0.79	0.90	0.88	0.95
Redundancies	0.42	0.48	0.59	0.69	0.76	0.85	0.88	0.94

Note. See notes in Table 6 and C1.
Source: Own calculations.

Table C6. RMSE for CPIF inflation

Evaluation period 2013Q1–2019Q4

Quarter	1	2	3	4	5	6	7	8
Univariate	*0.28*	*0.35*	*0.42*	*0.49*	*0.49*	*0.53*	*0.55*	*0.57*
Naive forecast	*0.27*	*0.34*	*0.40*	*0.49*	*0.52*	*0.59*	*0.67*	*0.77*
Mean_12	*0.55*	*0.61*	*0.68*	*0.74*	*0.78*	*0.83*	*0.86*	*0.90*
BVAR(7)	*0.28*	*0.39*	*0.45*	*0.54*	*0.58*	*0.64*	*0.69*	*0.73*
BVAR(11)	*0.29*	*0.38*	*0.45*	*0.51*	*0.55*	*0.57*	*0.59*	*0.61*
Indicator of Economic Activity	0.27	0.35	0.41	0.47	0.48	0.50	0.53	0.55
Wage drift (12m)	0.27	0.34	0.41	0.47	0.48	0.52	0.53	0.56
Profitability	0.28	0.37	0.43	0.49	0.49	0.54	0.54	0.57
Price changes (12m)	0.28	0.35	0.44	0.51	0.52	0.55	0.58	0.59
OMX30	0.28	0.36	0.43	0.48	0.46	0.49	0.49	0.49
OMX all share	0.28	0.36	0.44	0.49	0.47	0.49	0.49	0.51
OMX mid cap	0.27	0.34	0.40	0.47	0.47	0.49	0.49	0.51
OMX small cap	0.27	0.34	0.40	0.45	0.44	0.47	0.47	0.50
EPU_Sweden	0.28	0.37	0.43	0.49	0.51	0.53	0.52	0.53
EPU_Global	0.28	0.38	0.46	0.51	0.52	0.53	0.53	0.54
Spread (10y 2y)	0.28	0.36	0.43	0.48	0.48	0.50	0.50	0.50
Spread (1y 3m)	0.28	0.36	0.42	0.48	0.48	0.51	0.50	0.50
FCI RB	0.26	0.34	0.43	0.48	0.49	0.51	0.50	0.50
VIX CBOE	0.28	0.36	0.43	0.49	0.48	0.51	0.49	0.50
VIX futures	0.27	0.35	0.40	0.47	0.47	0.50	0.51	0.53
Price plans (trade)	0.30	0.40	0.46	0.52	0.51	0.52	0.49	0.47
Price plans (services)	0.27	0.34	0.42	0.49	0.49	0.52	0.51	0.53
GSCPI	0.29	0.38	0.45	0.51	0.50	0.52	0.50	0.51
Redundancies	0.28	0.35	0.41	0.47	0.46	0.48	0.48	0.49

Note. See notes in Table 6 and C1.
Source: Own calculations.

Table C7. Relative forecast accuracy for GDP growth

The indicators are assumed to be available one quarter ahead of GDP.
Evaluation period: 2013Q1-2019Q4

Quarter	1	2	3	4	5	6	7	8
Univariate	*0.77*	*1.07*	*1.30*	*1.44*	*1.43*	*1.38*	*1.34*	*1.32*
BVAR(11)	*0.90*	*1.31*	*1.63*	*1.84*	*1.88*	*1.91*	*1.89*	*1.85*
Naive forecast	*0.81*	*1.17*	*1.48*	*1.75*	*1.81*	*1.78*	*1.75*	*1.74*
Mean_12	*1.47*	*1.52*	*1.55*	*1.58*	*1.55*	*1.51*	*1.46*	*1.40*
Indicator of Economic Activity	0.73	1.01	1.20	1.32	1.39	1.39	1.37	1.33
Investment plans (6m)	0.79	1.05	1.21	1.27	1.22	1.25	1.20	1.20
OMX30	0.75	1.01	1.21	1.30	1.34	1.32	1.22	1.18
OMX all share	0.69	0.81	0.99	1.21	1.32	1.38	1.39	1.30
OMX small cap	0.73	0.87	1.02	1.18	1.26	1.30	1.30	1.26
VIX CBOE	0.78	0.96	1.11	1.32	1.40	1.34	1.13	1.05
FCI RB	0.76	1.00	1.23	1.40	1.47	1.54	1.57	1.55
Confidence indicator (tot)	0.76	1.02	1.20	1.34	1.34	1.29	1.27	1.23
GSCPI	0.80	1.09	1.29	1.41	1.42	1.37	1.37	1.35
Redundancies	0.75	1.00	1.21	1.29	1.25	1.24	1.17	1.20

Note. See notes in Table 6 and C1.
Source: Own calculations.

Table C8. Relative forecast accuracy for employment growth

The indicators are assumed to be available one quarter ahead of employment.
Evaluation period: 2013Q1-2019Q4

Quarter	1	2	3	4	5	6	7	8
Univariate	*0.44*	*0.50*	*0.61*	*0.72*	*0.74*	*0.84*	*0.84*	*0.91*
BVAR(11)	*0.44*	*0.49*	*0.61*	*0.75*	*0.76*	*0.83*	*0.82*	*0.84*
Naive forecast	*0.45*	*0.51*	*0.61*	*0.74*	*0.74*	*0.89*	*0.88*	*0.92*
Mean_12	*0.58*	*0.60*	*0.63*	*0.65*	*0.67*	*0.70*	*0.70*	*0.72*
Indicator of Economic Activity	0.43	0.49	0.60	0.71	0.73	0.83	0.83	0.90
Investment plans (6m)	0.43	0.46	0.56	0.69	0.78	0.92	0.94	1.02
OMX30	0.43	0.52	0.60	0.71	0.77	0.87	0.93	1.00
OMX all share	0.43	0.51	0.60	0.68	0.73	0.81	0.80	0.87
OMX small cap	0.44	0.48	0.57	0.72	0.77	0.91	0.94	0.99
VIX CBOE	0.44	0.48	0.57	0.70	0.73	0.85	0.89	0.94
FCI RB	0.43	0.43	0.43	0.59	0.61	0.73	0.79	0.84
Confidence indicator (tot)	0.44	0.48	0.59	0.71	0.72	0.85	0.82	0.92
GSCPI	0.44	0.52	0.61	0.73	0.76	0.87	0.87	0.94
Redundancies	0.45	0.52	0.61	0.74	0.77	0.90	0.86	0.93

Note. See notes in Table 6 and C1.
Source: Own calculations.

Table C9. Relative forecast accuracy for CPIF inflation

The indicators are assumed to be available one quarter ahead of the CPIF.
Evaluation period: 2013Q1-2019Q4

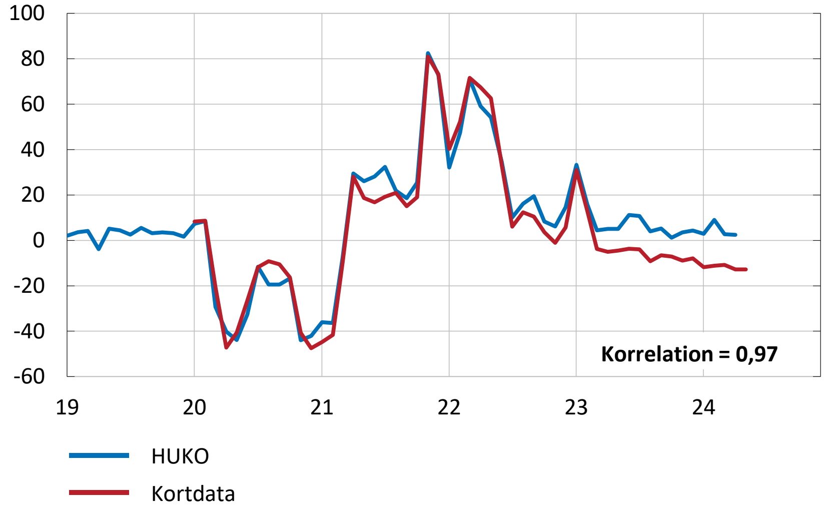
Quarter	1	2	3	4	5	6	7	8
Univariate	*0.28*	*0.35*	*0.43*	*0.48*	*0.48*	*0.49*	*0.49*	*0.50*
BVAR(11)	*0.29*	*0.38*	*0.45*	*0.51*	*0.55*	*0.57*	*0.59*	*0.61*
Naive forecast	*0.27*	*0.34*	*0.40*	*0.49*	*0.52*	*0.59*	*0.67*	*0.77*
Mean_12	*0.55*	*0.61*	*0.68*	*0.74*	*0.78*	*0.83*	*0.86*	*0.90*
Indicator of Economic Activity	0.28	0.34	0.42	0.47	0.47	0.48	0.48	0.49
Investment plans (6m)	0.27	0.33	0.40	0.46	0.48	0.52	0.54	0.59
OMX30	0.27	0.34	0.41	0.48	0.49	0.53	0.55	0.60
OMX all share	0.27	0.34	0.43	0.49	0.50	0.52	0.52	0.54
OMX small cap	0.28	0.36	0.44	0.49	0.48	0.49	0.49	0.49
VIX CBOE	0.27	0.35	0.43	0.49	0.47	0.48	0.48	0.48
FCI RB	0.27	0.34	0.41	0.47	0.46	0.49	0.49	0.50
Confidence indicator (tot)	0.27	0.36	0.42	0.48	0.48	0.51	0.49	0.49
GSCPI	0.27	0.34	0.41	0.45	0.43	0.43	0.41	0.39
Redundancies	0.27	0.35	0.41	0.47	0.47	0.49	0.48	0.50

Note. See notes in Table 6 and C1.
Source: Own calculations.

Appendix D - HUKO and card data for different consumption areas

Diagram 2. Restaurants, cafés and accommodation, HUKO and card data

Annual percentage change

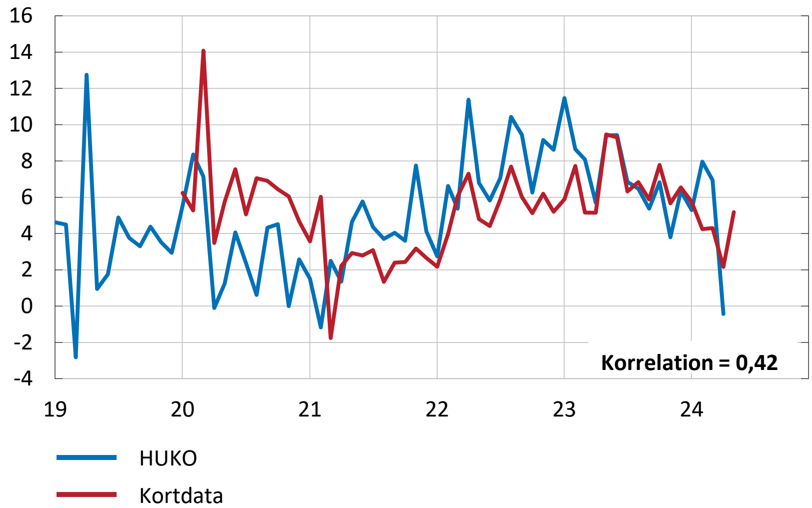


Note. See note in Chart 1.

Sources: Statistics Sweden and Swedbank.

Diagram 3. Food and drink, HUKO and card data

Annual percentage change

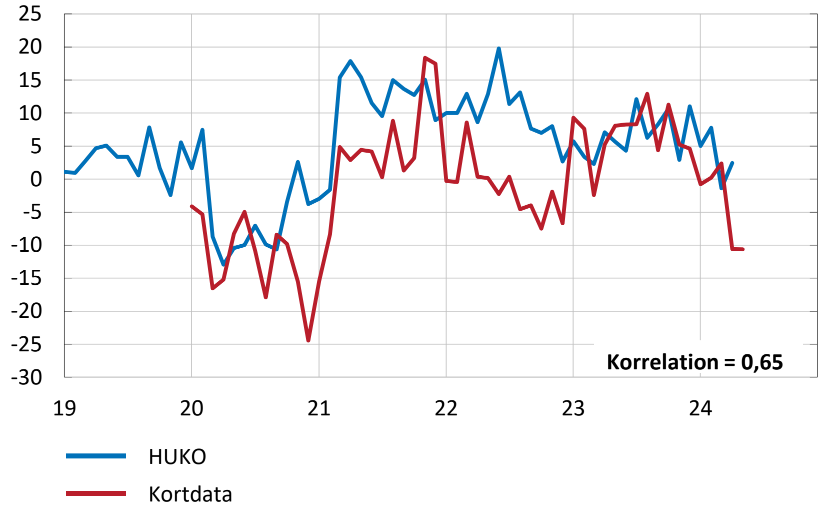


Note. See note in Chart 1.

Sources: Statistics Sweden and Swedbank.

Diagram 4. Recreation and culture, goods and services, HUKO and card data

Annual percentage change

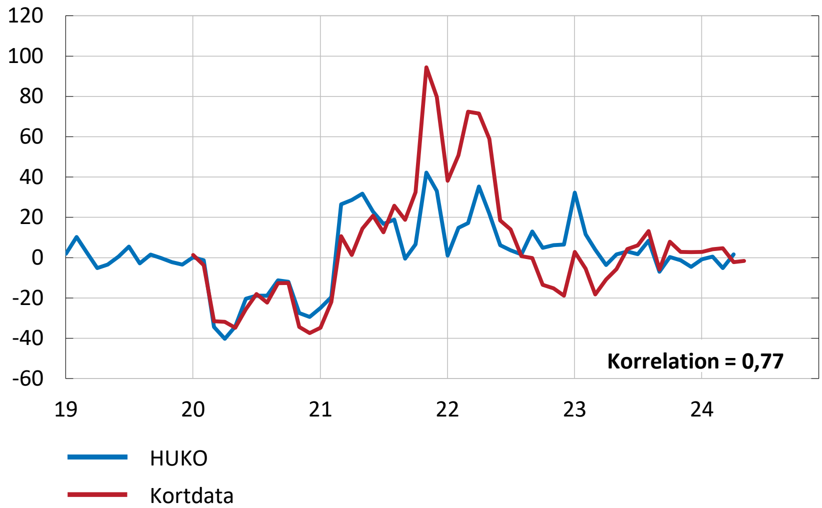


Note. See note in Chart 1

Sources: Statistics Sweden and Swedbank.

Diagram 5. Clothing and footwear, HUKO and card data

Annual percentage change

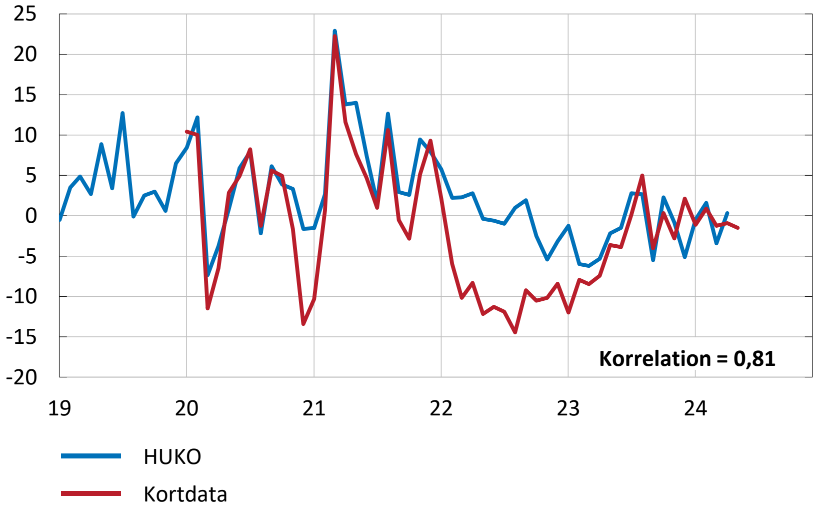


Note. See note in Chart 1.

Sources: Statistics Sweden and Swedbank.

Diagram 6. Furniture, equipment and consumables, HUKO and card data

Annual percentage change



Note. See note in Chart 1.

Sources: Statistics Sweden and Swedbank.

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