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Security through stability.

Contents

The instability of leading indicators in forecasting Austrian inflation: lessons from the COVID-19 pandemic and the energy crisis

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This analysis tests 25 macroeconomic indicators for their ability to predict Austrian HICP inflation and evaluates three methods of combining these indicators into a composite forecast. The key findings are:

First, for the evaluation period from early 2007 to the fourth quarter of 2023, competitors' import prices, oil prices and domestic output prices for consumer goods are found to be the best individual leading indicators across various forecasting horizons (one, four and eight quarters ahead).

Second, indicator performance varies over time. The forecasting performance of the output gap, for instance, declined considerably during the COVID-19 pandemic and the energy crisis, while that of other indicators like oil prices and competitors' import prices improved.

Third, for the period before 2020, composite indicators produced better forecasts than individual indicators over the entire forecasting horizon. This no longer holds when we include the pandemic and the energy crisis in the evaluation period. Then, two of the top three individual indicators, namely competitors' import prices and domestic output prices for consumer goods, outperform combined indicators over the medium- and longer-term horizon (four and eight quarters ahead).

Fourth, both individual and composite indicators outperformed autoregressive forecasts, especially in medium- and long-term predictions.

JEL classification: C53, E37, C50
Keywords: macroeconomic forecasting, inflation, leading indicators, forecast combination

Four times a year (in March, June, September and December), the Oesterreichische Nationalbank (OeNB) produces its Economic Outlook for Austria, aimed at guiding policymaking in general and at assessing price stability in particular. With respect to inflation forecasting, these projections employ time series models along the lines of Fritzer, Moser and Scharler (2002) as well as semistructural models. In the time between projection rounds, new economic indicators are published continuously. For forecasting inflation and evaluating current price stability alike, it is important to have a solid basis for assessing the information content indicators have for these purposes. One way to do this is to apply autoregressive distributed lag models in which inflation is explained by its own lags and the lags of individual indicators. Influential studies on the use of univariate leading indicators in forecasting inflation were carried out for the United States and the euro area by Cecchetti et al. (2000), Banerjee and Marcellino (2006) and Banerjee et al. (2005). The present study is based on these papers and tries to examine leading indicator properties for predicting Austrian inflation.[2] Furthermore, we assess the robustness of these indicators over time and explore the question whether there are reliable indicators that could predict the rapid surge of inflation in the period after 2021 and its downturn from the beginning of 2023.

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[2] The literature identifies several requirements an economic variable must fulfill to qualify as a useful leading indicator, one requirement being prompt availability without major later revisions (see Marcellino, 2006). This requirement is not fulfilled in our evaluation as we base our analysis on final indicator data.

Indicators frequently send diverse signals in terms of the strength and direction of inflation prospects. This makes it complicated to assess whether inflation is about to go up, fall or stabilize. Therefore, it might prove advantageous to condense the information content of a number of indicators into an aggregate (or composite indicator). Bates and Granger (1969) were perhaps the most influential researchers to spread the idea of combining leading indicator forecasts. There are different ways to do this.

- One – theoretically ideal – way would be to weight indicators according to their forecasting errors or, more specifically, to weight them proportionally to the inverse of their forecasting error variance, an approach which would downweigh indicators with large forecasting errors.
- A much simpler weighting scheme would be to attach equal weights to leading indicator forecasts. Surprisingly, some researchers found that the simple average of leading indicator forecasts proved to be more successful than more sophisticated weighting schemes (see e.g. Stock and Watson, 2004). This phenomenon has been described as the "forecast combination puzzle."
- Another way to summarize the information content of many indicators would be to first condense the information they contain into a few factors and then use these factors to forecast inflation. Stock and Watson (1999), for instance, used such factor models to forecast US inflation.

This paper also investigates these three composite indicators with respect to their accuracy in forecasting inflation in Austria. It is structured as follows: In the first section, we present the data used. In section 2, we describe inflation forecasts based on individual indicators in terms of their construction. Furthermore, we assess indicators' forecasting accuracy. Section 3 deals with the construction of composite leading indicators and their forecasting quality. Section 4 concludes.

1 Data

In total, we investigate 25 macroeconomic indicators (see table 1) that are forecast in the OeNB's regular macroeconomic projection exercises. Therefore, they provide a solid basis for a consistent inflation forecasting framework, as we will show in section 2. These indicators comprise price and cost indicators (e.g. oil prices, domestic output prices for consumer goods, compensation per employee), indicators of macroeconomic activity (e.g. real GDP, the output gap and the unemployment gap as measures of the degree of capacity utilization) and financial market indicators. The link between indicators of macroeconomic activity and inflation is likely to be tight in cases in which these variables are good measures of capacity utilization and in which inflation is determined from the demand side. Inflation tends to rise with the degree of utilization of production factors. Financial indicators are potentially useful predictors of inflation as they are inherently forward looking and reflect the transmission of monetary policy (e.g. interest rate changes).

Table 1

Leading indicators of inflation

Name of indicator
GDP deflator
Real private consumption
Compensation per employee
Unit labor costs (ULC)
Real investment
Total employment
Nominal effective exchange rate of the euro (export side)
Nominal effective exchange rate of the euro (import side)
Foreign demand
Competitors' import prices
Consumer loans
Loans to businesses
Real GDP
Productivity per employee
Unemployment rate
Non-accelerating inflation rate of unemployment (NAIRU)
Potential GDP
Long-term interest rate
Lending rate to businesses
Unemployment gap
Output gap
Profit margin
Oil price, EUR
USD-EUR exchange rate
Domestic output price index (consumer goods)

Source: Statistics Austria, Austrian Insitute of Economic Research (WIFO).

We use quarterly data from Q1 99 to Q4 23. Most of the data used in this empirical analysis are seasonally adjusted, except for oil prices, USD-EUR exchange rates, interest rates, domestic output prices and the inflation rate as measured by the Harmonised Index of Consumer Prices (HICP), as there is no or little seasonality in these variables. However, the modeling approach explained in section 2 effectively accounts for seasonality as well. In this empirical analysis, the variables interest rates, output gap, profit margin, unemployment rate, non-accelerating inflation rate of unemployment (NAIRU), i.e. the lowest unemployment rate consistent with stable inflation in the long run, and the unemployment gap are used in levels. All other variables are transformed into annual percentage changes.

2 Inflation forecasts based on individual indicators

To measure the informational content of individual indicators, we estimated an empirical specification to best represent the relationship between HICP inflation and each individual inflation indicator.

More specifically, we estimated an autoregressive distributed lag (ARDL) model of the form

$$\pi_t = \alpha + \sum_{k=1}^{4} \beta_k \pi_{t-k} + \sum_{q=0}^{4} \gamma_q x_{t-q} + \varepsilon_t, \qquad (1),$$

using the ordinary least squares method, where π is the annual inflation rate, x is the inflation indicator, ε an independent and identically distributed (IDD) disturbance term, *t* the time subscript and *t–k* and *t–q* are the *k*-times and *q*-times lagged value of the variables.[3] In a first step, the maximum lag lengths for inflation and the inflation indicators was restricted to be four, as we deal with quarterly data. In a second step, we chose the optimal lag specification of inflation and the inflation indicators to minimize the Akaike information criterium.[4] Lagged values of the annual inflation rate account for serial correlation in the variable, while lagged values of the indicators measure information content with respect to explaining inflation. As a benchmark, we also use an autoregression that only uses past inflation to forecast inflation.[5] For an indicator to be useful in inflation forecasting, its ARDL forecast must beat the autoregressive forecast. To conduct inflation forecasts based on indicators, we must have an estimate of how these indicators will develop over the forecasting period. We use the realized values of these indicators. This is certainly a strong assumption, however – an assumption that allows us to isolate the information content of the indicators with respect to forecasting inflation. The results of our forecast evaluation exercise must be interpreted against this background, as some indicators are inherently difficult to forecast (e.g. USD-EUR exchange rates and oil prices) or can be subject to significant data revisions. In our forecasting practice, however, we would use projected variables derived from the OeNB's macroeconometric model of the Austrian economy.

This framework is used to forecast Austrian inflation one to eight quarters ahead in the following way: Our forecast evaluation exercise involves non-overlapping estimation and forecasting periods such that only data from before the forecasting date are used in the estimation to produce out-of-sample forecasts. More specifically, in a first step, the estimation equation is determined for the period from Q1 99 to Q1 07, followed by a forecast of the HICP inflation rate up to eight quarters ahead (from Q2 07 to Q1 09). Subsequently, the relationship between the indicator used and HICP inflation is estimated for the first period plus one quarter and an inflation forecast is conducted for the period up to eight quarters ahead. This procedure is repeated until the entire forecast evaluation period (Q2 07 to Q4 23) is covered. It results in 67 one-quarter-ahead forecasts, 64 four-quarters-ahead forecasts and 60 eight-quarters-ahead forecasts, which are then compared with the realized values. Forecasting accuracy is measured using the root mean squared prediction error (RMSPE), which assesses the average deviation of the forecast from the actual outcome.[6]

[3] The estimation is performed in EViews. The software routine applied allows a lag of zero for the independent variable. This might occasionally overestimate the information content of indicators as many macroeconomic variables are published with a delay.

[4] We investigate 20 different lag specifications with a maximum lag length of four, i.e. k=1 to 4 and q=0 to 4.

[5] We used an autoregressive process of order 2 (AR(2)) that was fixed. Model adequacy was checked for the entire sample only.

[6] We chose the RMSPE because it is one of the most popular accuracy measures. All accuracy measures have pros and cons. Two arguments in favor of the RMSPE are that it penalizes larger errors more than smaller errors and that it is readily interpretable as it has the same scale as the target variable (i.e. the annual inflation rate).

Table 2.1

Indicators' HICP inflation forecasting performance (Q2 07 to Q4 19)

	Ranking[1] per forecasting horizon		
	One quarter ahead	Four quarters ahead	Eight quarters ahead
GDP deflator	23	12	24
Real private consumption	22	11	13
Compensation per employee	18	16	10
Unit labor costs (ULC)	25	22	11
Real investment	9	7	18
Total employment	8	10	3
Nominal effective exchange rate of the euro (export side)	21	19	16
Nominal effective exchange rate of the euro (import side)	17	20	14
Foreign demand	5	3	5
Competitors' import prices	14	6	2
Consumer loans	12	15	12
Loans to businesses	19	8	7
Real GDP	24	23	23
Productivity per employee	13	21	6
Unemployment rate	11	9	9
Non-accelerating inflation rate of unemployment (NAIRU)	10	13	19
Potential GDP	20	25	25
Long-term interest rate	7	18	22
Lending rate to businesses	4	5	15
Unemployment gap	6	4	8
Output gap	3	2	4
Profit margin	15	24	17
Oil price, EUR	2	14	21
USD-EUR exchange rate	16	17	20
Domestic output price index (consumer goods)	1	1	1

Source: Author's calculations, OeNB, Statistics Austria.

[1] The ranking is measured using the root mean squared preditcion error (RMSPE). Green cells show the five best-performing indicators, red cells the five worst-performing indicators per forecasting horizon.

Table 2.1 shows the results of the described evaluation process for three different forecasting horizons within the period from Q2 07 to Q4 19, i.e. without taking into account the COVID-19 shock and the energy price shock. Below, we investigate whether the results remain robust when these shocks are included in the evaluation period. Table 2.1 also gives the rank of the indicators according to the RMSPEs. These rankings must be interpreted against the background that RMSPEs occasionally differ only slightly from each other. In this analysis, we did not test whether there were any significant differences between RMSPEs. For the RMSPEs themselves, see tables A1.1 and A1.2 in the annex. Table 2.1 reports the forecasting performance of the examined indicators until end-2019.

For that period, domestic output prices for consumer goods are found to perform best, meaning that across all forecasting horizons, this inflation indicator provides the most accurate forecasts of the HICP inflation rate. Indicators that also show good forecasting qualities across all forecasting horizons include the output gap and foreign demand.[7] A partially good forecasting performance

[7] Sometimes, the RMSPEs of individual indicators differ only slightly, like e.g. the RMSPE of foreign demand from that of the autoregressive benchmark for the one-quarter-ahead horizon.

can be reported for the lending rate to businesses (one and four quarters ahead), competitors' import prices and total employment (eight quarters ahead) as well as oil prices (one quarter ahead). The euro-denominated oil price, for instance, is found to be among the best inflation indicators, but its forecasting performance is very good only for one-quarter-ahead forecasts and deteriorates significantly with the length of the forecasting horizon. For eight quarters ahead, it is even among the five worst inflation indicators examined. Conversely, competitors' import prices and total employment show good leading indicator properties over longer forecasting horizons (eight quarters ahead) but not for the shorter horizons of one quarter ahead and four quarters ahead. However, we must take into account that indicator performance is measured as an average across the entire forecasting period. This masks the possibility that large episodic errors might be mitigated over time. For instance, the output gap and domestic output prices for consumer goods considerably overestimated inflation developments in 2016 and 2017, as inflation during this period was largely driven by oil prices. Circumstances like these might call for a combination of indicators, which we investigate in section 3. When considering an autoregressive model of inflation as a benchmark, we find that 9 to 13 indicators beat autoregressions over the one- to eight-quarters-ahead forecasting horizon (see table A2.1 in the annex).

As a robustness check, we compared these results with the evaluation carried out over the period including the COVID-19 and energy crises. Extending the evaluation period until the end of Q4 23 changes the forecasting performance of indicators to some extent (see table 2.2).

Table 2.2

Indicators' HICP inflation forecasting performance (Q2 07 to Q4 23)

	Ranking[1] per forecasting horizon		
	One quarter ahead	Four quarters ahead	Eight quarters ahead
GDP deflator	18	22	25
Real private consumption	25	19	15
Compensation per employee	12	11	5
Unit labor costs (ULC)	21	24	24
Real investment	22	21	21
Total employment	5	10	8
Nominal effective exchange rate of the euro (export side)	17	20	17
Nominal effective exchange rate of the euro (import side)	15	16	12
Foreign demand	7	5	10
Competitors' import prices	2	1	1
Consumer loans	14	18	19
Loans to businesses	19	15	14
Real GDP	23	17	16
Productivity per employee	11	12	20
Unemployment rate	13	13	13
Non-accelerating inflation rate of unemployment (NAIRU)	9	8	4
Potential GDP	20	25	23
Long-term interest rate	8	6	6
Lending rate to businesses	10	9	7
Unemployment gap	4	7	11
Output gap	24	4	9
Profit margin	6	14	18
Oil price, EUR	1	3	3
USD-EUR exchange rate	16	23	22
Domestic output price index (consumer goods)	3	2	2

Source: Author's calculations, OeNB, Statistics Austria.

[1] The ranking is measured using the root mean squared prediction error (RMSPE). Green cells show the five best-performing indicators, red cells the five worst-performing indicators per forecasting horizon.

Comparing RMSPEs for the entire evaluation period (until Q4 23) with those for the period until Q4 19, shows that their levels increase substantially for almost all indicators (compare tables A1.1 and A1.2 in the annex). Part of this increase is attributable to the fiscal measures that were introduced in Austria in 2022 and 2023 to dampen energy price inflation[8], given that these measures are not accounted for in our forecast evaluation exercise. According to our estimates, the impact of the fiscal measures on Austria's HICP inflation amounted to –0.4 percentage points in 2022 and –0.9 percentage points in 2023.

Competitors' import prices are the best indicator over the entire forecasting period. However, oil prices and domestic output prices of consumer goods perform well for one, four and eight quarters ahead too. Compared with the period until Q4 19, the forecasting performance of competitors' import prices and of oil prices improved. In the period until Q4 19, oil prices only performed well for one-quarter-ahead forecasts and competitors' import prices did so only for four- and eight-quarters-ahead forecasts. Domestic output prices for consumer goods maintained

[8] These measures included the reduction of the natural gas and electricity tax in 2022 and 2023, the suspension of the renewable energy subsidy in 2022 and 2023 and the electricity price cap in place since December 2022.

their good forecasting performance but fell behind competitors' import prices in particular when measured in terms of RMSPEs (see tables A1.1 and A1.2). The output gap lost its good leading indicator properties for the short term (one quarter ahead) forecast when compared to the evaluation for the period until Q4 19 but maintained relatively good forecasting properties for the medium term forecast (four quarters ahead). However, we must not forget that extending the evaluation period from Q4 19 to Q4 23 implies that only few observations are available for the four-quarters-ahead horizon (13) and even less for the eight-quarters-ahead horizon (10).

When comparing the performance of individual indicators with the benchmark of an autoregressive process that only uses past inflation to forecast inflation, we find that the longer the forecasting horizon the better the forecasting accuracy of the individual indicators as long as the entire period until end-2023 was evaluated (see tables A1.1 and A1.2). This was not the case for the shorter evaluation period until end-2019. Hence, we can conclude that during the COVID-19 pandemic and the energy crisis, the autoregressive benchmark deteriorated in comparison to the forecasting performance of the individual indicators. This may partly be due to our forecast evaluation framework, which uses realized values for the individual indicators. In times of shocks, when indicators change more strongly than in normal times, advance information on the development of variables becomes more important. Autoregressive processes, by contrast, use only past information. This might be sufficient for inflation forecasting in normal times but less so in turbulent times.

3 Inflation forecasts based on composite indicators

Building on our evaluation of individual indicators, we explore the question whether their information content can be combined into composite indicators that are superior to individual indicators. Forecasts based on indicator combinations might outperform individual indicator forecasts as they pool the information contained in a number of indicators. Furthermore, Clements and Hendry (2002) showed that structural breaks might be tackled by way of combining indicators, as breaks may affect specific indicators more than others. For instance, the problems with measuring the output gap during the COVID-19 pandemic were not mirrored to the same extent in the development of domestic output prices for consumer goods. In this forecast evaluation exercise, we test three commonly used composite indicators: (1) the simple average of all leading indicator forecasts; (2) the optimal weighting of individual indicator forecasts based on their prediction errors according to Bates and Granger (1969). More specifically, this means that indicator i (one of the indicators in table 1) is weighted proportionally to the inverse of its squared prediction error σ_i^2 , i.e.

$$w_i = \frac{1/\sigma_i^2}{\sum_i \frac{1}{\sigma_i^2}} \qquad (2).$$

In our empirical investigation, the forecast evaluation is conducted in a recursive manner (see section 2), constantly updating the weights; and (3) the aggregation of indicators using factor analysis. This is a statistical technique that condenses a large number of indicators into one or a few summary measures. The first summary measure (the so-called first factor) is defined as the linear combination of the indicators which explains most of the variability of the indicators. We therefore choose this first summary measure in our forecasting exercise. This technique is applied i.a. by Stock and Watson (1999). The first two composite indicators listed above combine inflation forecasts while the third combines indicators into a summary measure which is subsequently used in forecasting inflation. Our selection of these combination methods is by no means arbitrary. The simple average deserves attention as it sometimes proves superior to other aggregates in empirical studies. In a recent survey on forecast combinations, Wang et al. (2023) stated, "Despite the explosion of various popular and sophisticated combination methods, empirical evidence and extensive simulations repeatedly show that the simple average with equal weights often outperforms more complicated weighting schemes." From a theoretical point of view, forecast combinations based on optimal weights according to Bates and Granger (1969) are, however, superior to the simple average with equal weights, and forecasts using factor models are an acknowledged method for working with many variables.

Table 3.1 shows the forecasting performance of the three composite indicators in question as well as the forecasting errors of some of the best individual indicators for the evaluation period from Q2 07 to Q4 19. The volatile period driven by the COVID-19 and energy crises is evaluated in a subsequent step.

Table 3.1

Indicators' HICP inflation forecasting errors (Q2 07 to Q4 19)

	Forecasting horizon		
	One quarter ahead	Four quarters ahead	Eight quarters ahead
Combined indicators			
First factor extracted using factor analysis	0.34	0.66	0.54
Weighted average according to Bates and Granger	0.43	0.95	0.71
Arithmetic mean of individual indicators	0.43	1.01	0.83
Selected best-performing individual indicators			
Domestic output prices for consumer goods	0.42	0.87	0.72
Output gap	0.45	0.93	0.83
Oil price, EUR	0.43	1.19	1.16

Source: Author's calculations.

Note: The forecasting error is measured using the root mean squared prediction error (RMSPE).

During the period until the end of 2019, the first factor extracted from the 25 variables specified in table 1 is the best-performing composite indicator. It puts most of the weight (referred to as "loading") on oil prices, followed by a wide margin by the unemployment rate and foreign demand. Next in line with roughly equal weights are consumer loans, competitors' import prices, loans to consumers and businesses, real investment and real GDP.[9] We find that across all forecasting horizons, the first factor scheme consistently outperforms both the simple average scheme and the composite indicator scheme according to Bates and Granger (1969). Bates and Granger weights are equal to the simple arithmetic mean for one-quarter-ahead forecasts but much better for longer forecasting horizons. Therefore, the so-called forecast combination puzzle is not supported for this period. Additionally, we find that the best individual indicators lag significantly behind the first component derived from the factor analysis for the medium- and long-term forecasting horizon (four quarters ahead and eight quarters ahead). Comparing the results of the equal weighting scheme and the optimal weighting scheme with the best individual indicator forecasts shows that the weighting combination schemes prove to be broadly equal for

[9] This applies to the estimation period from Q1 99 to Q4 19. Factors and loadings change over time.

the short-term horizon of one quarter ahead while over the long-term horizon of eight quarters ahead, they tend to be slightly better.

Table 3.2 reports the results we obtained when including the COVID-19 pandemic and the energy crisis in our evaluation of indicators' forecasting performance.

Table 3.2

Indicators' HICP inflation forecasting errors (Q2 07 to Q4 23)

	Forecasting horizon		
	One quarter ahead	Four quarters ahead	Eight quarters ahead
Combined indicators			
First factor extracted using factor analysis	0.41	1.57	2.26
Weighted average according to Bates and Granger	0.57	2.02	2.23
Arithmetic mean of individual indicators	0.58	2.18	2.43
Selected best-performing individual indicators			
Domestic output prices for consumer goods	0.47	1.43	1.94
Competitors' import prices	0.46	1.37	1.85
Oil price, EUR	0.45	1.77	2.41

Source: Author's calculations.

Note: The forecasting error is measured using the root mean squared prediction error (RMSPE).

When we compare the size of the forecasting errors reported in table 3.2 with those for the period until end-2019, we find that the forecasting performance of individual indicators and combined indicators worsens.

For four-quarters-ahead and eight-quarters-ahead forecasts, individual indicators surpassed the forecasting performance of the first factor extracted using factor analysis, while the first factor performs best only over the short run (one quarter ahead). Over the entire forecasting horizon, the weighting combination schemes yielded less accurate results than the two best individual indicators (competitors' import prices and domestic output prices for consumer goods). So in this case, the combined indicators did not prove to be a hedge against structural breaks. However, the good results in terms of forecasting accuracy for individual indicators that we recorded over the entire evaluation period until end-2023 must be interpreted against the background of the large size of the forecasting errors. The failure of the composite indicator forecasts to outperform individual indicator forecasts in an unstable environment calls for an investigation into the reasons, which might help improve the forecasting performance of composite indicators. One reason could be that the accuracy of individual indicator forecasts changes over time. In that case, the weights of indicators with a deteriorating forecasting accuracy will need to be downgraded.

4 Conclusions

In this analysis, 25 macroeconomic indicators were tested for their leading indicator properties concerning the Austrian HICP inflation rate. Additionally, we evaluated three methods that combine the information content of these indicators with the purpose of forecasting inflation. One major result is that leading indicator properties change over time. For instance, international commodity prices (oil prices, import prices) became more important as leading indicators after Q1 00, while economic activity variables (output gap, unemployment gap) lost their leading indicator properties with respect to HICP inflation. Structural changes during the COVID-19 and energy price shocks seem to be key events that changed indicators' forecasting performance. An update of indicators in use in inflation forecasting practice therefore seems to be warranted, in particular when it comes to accounting for potential economic shocks. During economically more tranquil periods, we could continue to rely on established indicators.

Overall, our analysis might provide useful inputs to monitoring inflation developments. In particular, the forecasting framework using individual and composite indicators may generate information complementary to that produced by other models and may thus prove helpful in projection exercises.

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Annex

Table A1.1

Indicators' root mean squared prediction errors (Q2 07 to Q4 19)

	Forecasting horizon		
	One quarter ahead	Four quarters ahead	Eight quarters ahead
GDP deflator	0.52	1.18	1.44
Real private consumption	0.51	1.15	0.98
Compensation per employee	0.50	1.23	0.93
Unit labor costs (ULC)	0.56	1.39	0.94
Real investment	0.47	1.13	1.07
Total employment	0.47	1.14	0.82
Nominal effective exchange rate of the euro (export side)	0.51	1.29	1.01
Nominal effective exchange rate of the euro (import side)	0.50	1.29	1.01
Foreign demand	0.46	1.00	0.84
Competitors' import prices	0.49	1.06	0.78
Consumer loans	0.48	1.19	0.94
Loans to businesses	0.51	1.13	0.90
Real GDP	0.55	1.43	1.27
Productivity per employee	0.49	1.29	0.90
Unemployment rate	0.48	1.14	0.93
Non-accelerating inflation rate of unemployment (NAIRU)	0.48	1.18	1.07
Potential GDP	0.51	1.82	2.33
Long-term interest rate	0.46	1.28	1.22
Lending rate to businesses	0.45	1.03	1.01
Unemployment gap	0.46	1.03	0.91
Output gap	0.45	0.93	0.83
Profit margin	0.50	1.44	1.02
Oil price, EUR	0.43	1.19	1.16
USD-EUR exchange rate	0.50	1.26	1.10
Domestic output price index (consumer goods)	0.42	0.87	0.72
First factor extracted using factor analysis	0.34	0.66	0.54
Combined forecast (Bates and Granger)	0.43	0.95	0.71
Combined forecast (simple average)	0.43	1.01	0.83
AR(2) model (benchmark)	0.46	1.15	0.92

Source: Author's calculations.

Note: AR(2) indicates an autoregressive process of order 2.

Table A1.2

Indicators' root mean squared prediction errors (Q2 07 to Q4 23)

	Forecasting horizon		
	One quarter ahead	Four quarters ahead	Eight quarters ahead
GDP deflator	0.57	2.17	3.22
Real private consumption	0.67	2.07	2.58
Compensation per employee	0.54	1.94	2.42
Unit labor costs (ULC)	0.58	2.20	3.00
Real investment	0.60	2.12	2.65
Total employment	0.51	1.94	2.43
Nominal effective exchange rate of the euro (export side)	0.56	2.10	2.60
Nominal effective exchange rate of the euro (import side)	0.55	2.01	2.55
Foreign demand	0.51	1.86	2.49
Competitors' import prices	0.46	1.37	1.85
Consumer loans	0.55	2.07	2.62
Loans to businesses	0.57	1.99	2.56
Real GDP	0.61	2.06	2.59
Productivity per employee	0.53	1.94	2.63
Unemployment rate	0.54	1.98	2.55
Non-accelerating inflation rate of unemployment (NAIRU)	0.52	1.89	2.41
Potential GDP	0.58	2.26	2.75
Long-term interest rate	0.51	1.88	2.42
Lending rate to businesses	0.52	1.92	2.42
Unemployment gap	0.50	1.89	2.53
Output gap	0.62	1.85	2.48
Profit margin	0.51	1.99	2.60
Oil price, EUR	0.45	1.77	2.41
USD-EUR exchange rate	0.56	2.17	2.73
Domestic output price index (consumer goods)	0.47	1.43	1.94
First factor extracted using factor analysis	0.41	1.57	2.26
Combined forecast (Bates and Granger)	0.56	1.97	2.19
Combined forecast (simple average)	0.58	2.14	2.40
AR(2) model (benchmark)	0.53	2.05	2.61

Source: Author's calculations.

Note: AR(2) indicates an autoregressive process of order 2.

Table A2.1

Indicators' root mean squared prediction errors (Q2 07 to Q4 19)

	Forecasting horizon		
	One quarter ahead	Four quarters ahead	Eight quarters ahead
GDP deflator	1.13	1.03	1.56
Real private consumption	1.12	1.00	1.07
Compensation per employee	1.10	1.07	1.01
Unit labor costs (ULC)	1.22	1.21	1.01
Real investment	1.03	0.98	1.16
Total employment	1.02	1.00	0.89
Nominal effective exchange rate of the euro (export side)	1.11	1.12	1.09
Nominal effective exchange rate of the euro (import side)	1.09	1.12	1.09
Foreign demand	0.99	0.87	0.91
Competitors' import prices	1.07	0.92	0.85
Consumer loans	1.05	1.04	1.02
Loans to businesses	1.10	0.99	0.98
Real GDP	1.20	1.25	1.37
Productivity per employee	1.07	1.12	0.98
Unemployment rate	1.04	0.99	1.00
Non-accelerating inflation rate of unemployment (NAIRU)	1.04	1.03	1.16
Potential GDP	1.11	1.59	2.52
Long-term interest rate	1.00	1.12	1.32
Lending rate to businesses	0.98	0.90	1.09
Unemployment gap	1.00	0.89	0.99
Output gap	0.97	0.81	0.90
Profit margin	1.08	1.26	1.11
Oil price, EUR	0.93	1.04	1.26
USD-EUR exchange rate	1.09	1.10	1.19
Domestic output price index (consumer goods)	0.91	0.76	0.78
First factor extracted using factor analysis	**0.73**	**0.57**	**0.58**
Combined forecast (Bates and Granger)	0.93	0.83	0.77
Combined forecast (simple average)	0.93	0.88	0.89

Source: Author's calculations.

Note: RMSPEs as ratio to the AR(2) benchmark. Green cells indicate better performance than the AR(2) benchmark. Bold numbers indicate the best performer.

Table A2.2

Indicators' root mean squared prediction errors (Q2 07 to Q4 23)

	Forecasting horizon		
	One quarter ahead	Four quarters ahead	Eight quarters ahead
GDP deflator	1.07	1.06	1.23
Real private consumption	1.26	1.01	0.99
Compensation per employee	1.01	0.95	0.93
Unit labor costs (ULC)	1.09	1.08	1.15
Real investment	1.13	1.04	1.01
Total employment	0.96	0.95	0.93
Nominal effective exchange rate of the euro (export side)	1.06	1.03	0.99
Nominal effective exchange rate of the euro (import side)	1.03	0.98	0.98
Foreign demand	0.96	0.91	0.95
Competitors' import prices	0.86	**0.67**	**0.71**
Consumer loans	1.03	1.01	1.00
Loans to businesses	1.07	0.97	0.98
Real GDP	1.15	1.01	0.99
Productivity per employee	0.99	0.95	1.01
Unemployment rate	1.01	0.97	0.98
Non-accelerating inflation rate of unemployment (NAIRU)	0.98	0.92	0.92
Potential GDP	1.08	1.11	1.05
Long-term interest rate	0.96	0.92	0.93
Lending rate to businesses	0.98	0.94	0.93
Unemployment gap	0.94	0.92	0.97
Output gap	1.16	0.90	0.95
Profit margin	0.96	0.97	1.00
Oil price, EUR	0.85	0.86	0.92
USD-EUR exchange rate	1.05	1.06	1.05
Domestic output price index (consumer goods)	0.88	0.70	0.74
First factor extracted using factor analysis	**0.78**	0.77	0.86
Combined forecast (Bates and Granger)	1.06	0.96	0.84
Combined forecast (simple average)	1.08	1.04	0.92

Source: Author's calculations.

Note: RMSPEs as ratio to the AR(2) benchmark. Green cells indicate better performance than the AR(2) benchmark. Bold numbers indicate the best performer.

Recent inflation developments in Austria – an analysis based on different decomposition frameworks

Lukas Reiss and Martin Schneider[1]

In this paper we show that decomposing national accounts deflators such as the GDP deflator as a proxy for consumer price inflation can lead to misleading results. We compare the decomposition of the value-added deflator, the GDP deflator and the total supply deflator with a HICP decomposition proposed by Schneider (2024). We discuss the differences between these concepts in detail. We find that imports and wages account for the bulk of the differences. Most importantly, the surge in import prices in late 2021 pushed up HICP inflation but had no direct impact on the GDP deflator. Furthermore, we find that wage developments have a much higher impact on the GDP deflator than the HICP. In both 2023 and 2024, the contribution of wages to the GDP deflator was higher than for the HICP even though the latter index increased stronger in both years. We also look at the role of profits. While they were soaring in 2022 and contributed somewhat to inflation, they cratered in 2023 and particularly in 2024.

JEL classification: E31, D33
Keywords: inflation, profit share

Since mid-2021, consumer prices have increased substantially in the euro area, and even more so in Austria. Numerous studies have decomposed inflation to investigate potential sources and/or beneficiaries of high inflation. Most commonly, such papers look at the increase of the GDP deflator or the value-added deflator as a proxy for domestic price pressures (e.g. Arce et al., 2023, Fritzer et al., 2023, or Hahn, 2023) and decompose them into cost-side contributions of national accounts aggregates such as wages, net indirect taxes and depreciation and wages.

These decompositions are very simple and easy to calculate. However, the GDP deflator differs substantially from consumer prices. Particularly in the beginning of the high-inflation period, the GDP deflator increased much less than consumer prices. The main reason for this is that GDP only covers domestic production. Therefore, a decomposition of the GDP deflator cannot cover the effects of the strong increases in import prices that led to a substantial worsening of the terms of trade for the euro area member states. Overall, consumer prices are ultimately relevant for cost of living, and they are more important for both monetary and fiscal policy. The Harmonised Index of Consumer Prices (HICP) is used by the Eurosystem in its definition of price stability. The conceptually very similar national consumer price index is used in Austria as a reference point for agreements on the increase of private and public wages as well as for the indexation of social benefits (particularly pensions) and income tax brackets.

The importance of import prices has been accounted for in the works Diev et al. (2019) and Hansen et al. (2023), but we will show further significant differences between the GDP deflator and the HICP. We do so by linking information on cost structures from input-output tables with data from the quarterly national accounts. We investigate which cost components benefit from price increases, i.e. whether higher prices go into imports, wages, profits or taxes. For example, we can see to which extent the increase in energy inflation was accompanied by higher expenditure on energy imports and by higher profits of domestic energy producers.

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The paper is structured as follows: Section 1 gives an overview of the decomposition frameworks used in this analysis. Section 2 explains the differences between the HICP and the national accounts deflators in detail. Section 3 provides results concerning the decomposition of HICP inflation, including the role of profits. Section 4 concludes.

1 An overview of the decomposition frameworks

This section gives a brief overview of the different decomposition frameworks that we use in our analysis. We decompose the value-added deflator, the GDP deflator, the total supply deflator and the Harmonised Index of Consumer Prices (HICP) into cost components using national accounts data. We first outline the basic decomposition framework and then discuss the differences between the different price indices.

The decomposition is based on a simple accounting identity using quarterly national accounts data. We illustrate it using the value-added deflator ($p_{j,t}$) (see ECB, 2006, and Jaumotte and Morsy, 2012, for early applications). Nominal value added ($y_t^r p_t$) is defined as the sum of k nominal cost (income) components $cc_{k,t}$ (compensation of employees, taxes less subsidies on production, consumption of fixed capital and net operating surplus[2] (including mixed income)).

$$y_t^r p_t = \sum_{k=1}^{K} cc_{k,t} \tag{1}$$

Dividing this equation by real value added y_t^r, we obtain an equation which defines the value-added deflator as the sum of its per unit cost components ($ucc_{k,t}$).

$$p_t = \sum_{k=1}^{K} \frac{cc_{k,t}}{y_t^r} = \sum_{k=1}^{K} ucc_{k,t} \tag{2}$$

We now take the first difference and divide both sides of the equation by the previous period's value-added deflator. In addition, we expand each term of the right-hand side by unit costs observed in the previous period. The percentage change of the price of value added is hence defined as the sum of the percentage changes of its unit cost components weighted with the previous period's real unit cost component.

$$\frac{dp_t}{p_{t-1}} = \sum_{k=1}^{K} \frac{ducc_{k,t}}{ucc_{k,t-1}} \frac{ucc_{k,t-1}}{p_{t-1}} \tag{3}$$

It is straightforward to apply this decomposition to the other two deflators. For the GDP deflator, the list of cost components is augmented by taxes less subsidies on products (value-added tax, mineral oil tax, tobacco tax etc.). The concept of the total supply deflator was proposed by Hahn and Renault (2024). This approach tries to overcome the weakness of the first two approaches that use domestic value added or GDP instead of output. The reason is that quarterly national accounts do not include data on output. Instead, Hahn and Renault (2024) define the concept of "total supply" as the sum of GDP and imports as a proxy for output.

The decomposition of the HICP utilizes the decomposition framework developed by Schneider (2024). It is based on the same basic account identity but takes into account the differences in the structure between simple national accounts deflators and the HICP. It consists of two main parts. First, it uses input-output tables to derive the detailed cost structure of the HICP subindices at the

[2] Profits (net operating surplus) are not a cost component in a literal sense from a firm's perspective. For the sake of simplicity, however, we refer to them as a cost component.

COICOP-45 level. In the second main part, quarterly national accounts data and trade data are combined with the cost structure of the input-output tables. This is done in five steps: the first step is to estimate the cost components that are missing in quarterly national accounts.[3] In the second step, we adjust compensation of employees, profits and net other taxes on production for crisis-related subsidies.[4] In the third step, the share of the cost components implied by private consumption is isolated from other final uses and referred to as "consumption-implied cost components." The fourth step is to combine the cost components derived from the input-output table with growth rates of the consumption-implied cost components at the quarterly level. Finally, the last step is to decompose HICP inflation. This approach makes it possible to decompose HICP inflation into contributions stemming from value-added components per industry, taxes less subsidies on products, and imports. The annex provides more details on this approach.

Table 1 gives an overview of the cost components included in the different decomposition approaches.

Table 1

Overview of the cost components of different price indices

	Scope	Costs components					
		Compensation of employees	Taxes less subsidies		Consumption of fixed capital	Net operating surplus	Imports
			On production (other than on products)	On products			
Value-added deflator	Price index of domestic value added	X[1]	X[1]	-	X[1]	X[1]	-
GDP deflator	Price index of GDP	X[1]	X[1]	X[1]	X[1]	X[1]	-
Total supply deflator	Price index of total supply (= GDP + imports)	X[1]	X[1]	X[1]	X[1]	X[1]	X[1]
HICP	Harmonized Index of Consumer Prices	X[2]	X[2]	X[2]	X[2]	X[2]	X[2]

Source: Authors' compilation.

[1] *Total economy.*

[2] *Weighted sum of cost components based on weights from input-output tables and HICP weights.*

When interpreting results based on such decompositions, one has to keep in mind that one cannot infer causal relationships from identities. For example, high wage increases can, in different cases, be both the cause of high inflation (via pushing up costs) and the consequence of high inflation (via wage agreements based on inflation). Further caveats regarding our approach are discussed in chapter 7 of Schneider (2024).

[3] The published QNA data only contain value added and compensation of employees per industry. Therefore, we must estimate the three missing components (net taxes on production, consumption of fixed capital and net operating surplus), which are all published only at the total economy level. Details of the procedure can be found in Fritzer et al. (2023).

[4] From 2020 to 2022, the Austrian federal government paid out substantial subsidies to firms for short-time work, foregone revenue and increases in energy costs. These transfers led to a strong drop in net indirect taxes and have pushed up compensation of employees (short-time work subsidies) and net operating surplus (other subsidies). We have adjusted these three time series for these artificial breaks by subtracting these crisis subsidies from compensation of employees and net operating surplus. For a detailed description of these calculations see Fritzer et al. (2023).

2 A comparison of the decomposition of the HICP with different deflator decompositions

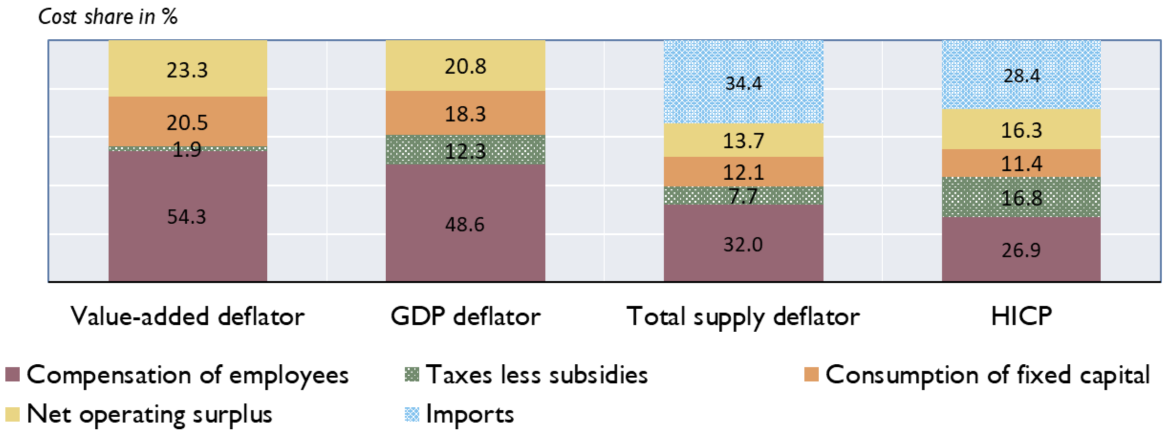
In this section we compare our four decomposition frameworks along two dimensions. First, we compare the cost structure (cost shares) for the year 2019.[5] Second, we compare the results of the decomposition for the period from 2019 until the third quarter of 2024.

2.1 Deflator concepts differ concerning the role of import prices

Chart 1 shows the cost structure of the three deflators and the HICP for the year 2019. For the *value-added deflator*, wages are the most important cost component with a share of 54.3%. The total cost share of firms (43.8%) equals the sum of consumption of fixed capital (20.5%) and net operating surplus (23.3%). The cost share of other taxes less subsidies on production (1.9%) is negligible. The *GDP deflator* has a very similar cost structure. The only difference is that the GDP deflator also includes taxes less subsidies on products, which have a cost share of 12.3%. Consequently, the cost shares of the other components fall, but their relative magnitude remains unchanged. The *total supply deflator* also includes imports, which are the most important cost component (34.4%). Once again, the role of the other cost components falls, but their relative magnitude remains constant.

Chart 1

Cost shares for three deflators and for headline HICP for Austria (2019)



Source: Statistics Austria, authors' calculations.

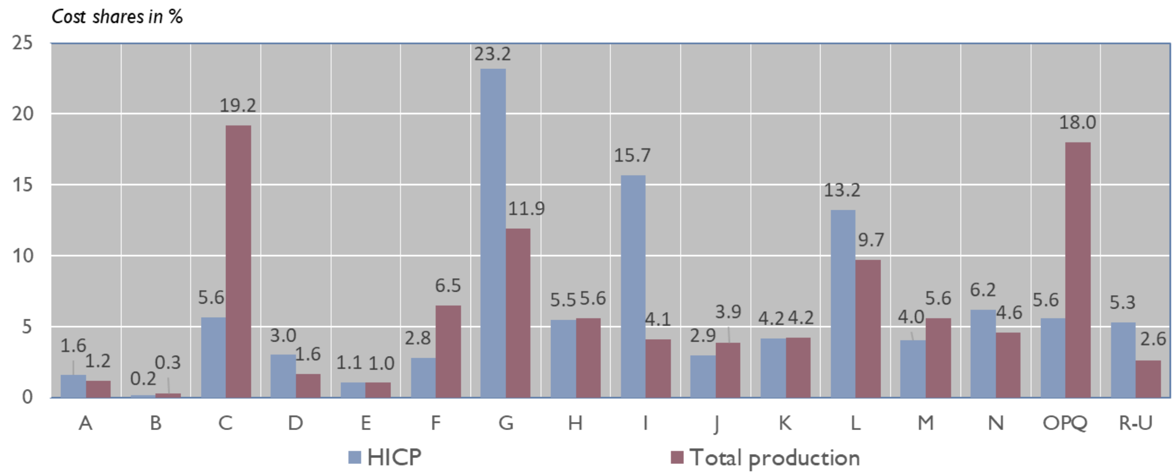
This picture changes when we look at the cost structure of the consumption bundle underlying the *HICP*. We can obtain the following differences: First, the cost share of wages (26.9%) is slightly lower than the share of gross operating surplus (= sum of net operating surplus and consumption of fixed capital) of 27.7%. This is a huge difference compared to the three other deflators, where the cost share of wages is considerably higher than that of gross operating surplus. This is due to the different roles of industries in the production of goods and services. For the three other deflators, total domestic production is considered, which serves all final demand

[5] We use the input-output table for the year 2019 for our analysis. Obviously, the cost structures have changed since then; first, due to the COVID-19 pandemic and, second, due to the massive increases of energy prices that followed. Our approach at least partly accounts for these structural changes since we use the cost structures from 2019 only as a starting point and update them with nominal national accounts data.

components. For the HICP, only the production of goods and services for private consumption is considered. Hence, the consumption bundle underlying the HICP has a different sectoral structure than total production (chart 2). The three industries that are much more important for private consumption than for total production are trade and repair of motor vehicles (G), accommodation and food services (I) and arts, entertainment, recreation and other private services (R-U). On the other hand, manufacturing (C), construction (F) and the public sector (OPQ) play a less important role for private consumption. Since the wage share of the public sector (75%) is much higher than the economy-wide wage share of 54%, wages are far less important for private consumption than for total production. This is also a very important factor when thinking about price-wage spirals: Wage agreements in Austria typically take past increases in the consumer price index (which has weights similar to the HICP) as a reference point. Ceteris paribus, a 1% increase in all wages raises the value-added deflator by 0.54 percentage points, the GDP deflator by 0.49 percentage points, but the HICP (similar to the CPI) only by 0.27 percentage points. This means that potential second-round effects of wage increases are much smaller than one would think based on the share of wages in GDP.

Chart 2

Cost shares of industries in domestic value added for total production and for the production of the consumption bundle underlying the HICP



Source: Statistics Austria, authors' calculcations.

Note: A: agriculture, forestry and fishing; B: mining and quarrying; C: manufacturing; D: energy; E: water and sewerage; F: construction; G: trade and repair of motor vehicles; H: transportation and storage; I: accommodation and food services; J: information and communication; K: finance and insurance activities; L: real estate activities; M: professional, scientific and technical activities; N: administrative and business support activities; OPQ: public sector activities; RTU: arts, entertainment, recreation and other private services.

Furthermore, the share of (net) indirect taxes is higher for the HICP. The value-added deflator does not include taxes and subsidies on products (e.g. VAT and energy taxes), and while GDP and total supply include them, their weight is still much lower than for consumption. The main reason is that a large share of the other final demand categories is exempted from VAT. Therefore, policies regarding indirect taxes and subsidies tend to have a larger effect on the HICP than on the GDP deflator.

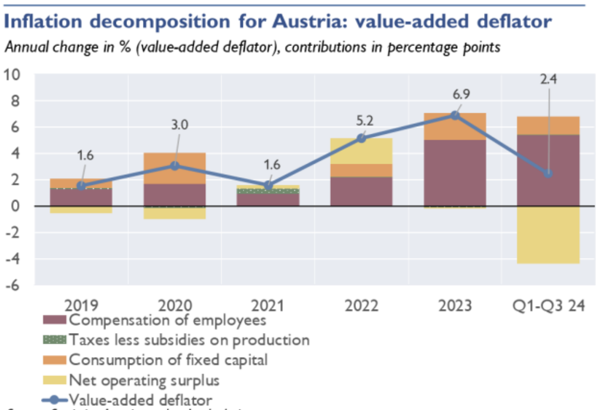
Moreover, compared to exports and gross fixed capital formation, private consumption comprises a much higher share of services. The services sectors have a higher share of self-employed persons (e.g. of profit earners) in employment than construction and manufacturing,[6] pushing up the share of net operating surplus.

2.2 The inflation shock affected the HICP sooner than the GDP deflator

Next, we look at the decomposition results for the different price concepts (chart 3). The decomposition of the HICP draws the picture of an initial import price shock, followed by substantial domestic price pressures. Imports were the main determinant of inflation in the years 2021 and 2022. In 2021, nonenergy imports were the strongest explanatory factor for inflation due to supply chain problems. In 2022, the largest contribution to inflation came from energy imports. The contribution of profits to inflation amounted to 27% in 2022, with the energy sector as the most important contributor[7]. Due to the lagged inflation adjustment of wages, their role as a cost factor for inflation (12%) was considerably below their cost share in the HICP (27%).

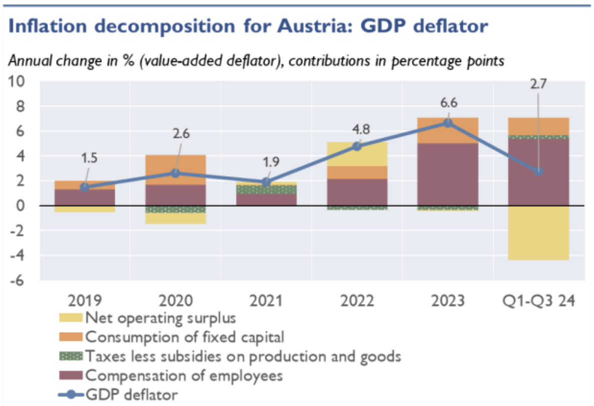
In 2023, the picture changed completely. Due the fall of energy and food prices, the contribution of imports vanished almost completely. Two domestic factors were the most important contributors: Driven by past inflation, the contribution of unit labor costs amounted to 60% of inflation. In addition, the replacement costs for the capital stock of firms (consumption of fixed capital) increased strongly in 2023 as a consequence of strong increases in the price of investment goods. The contribution of firms' profits fell to almost zero. In the first three quarters of 2024[8], inflation halved compared to 2023. As wage increases were strong and the contribution of consumption of fixed capital was still high, too, firms' unit profits fell sharply.

Chart 3.1



Source: Statistics Austria, authors' calculations.

Chart 3.2



[6] There are two important differences between the HICP consumption basket and private consumption expenditure: The former follows the domestic concept, while the latter looks at the resident population only. Therefore, the weight of restaurant and hotel services is much higher in the HICP. More importantly, private consumption is defined more broadly in terms of which services can be consumed. It also includes consumption of financial intermediation and particularly of imputed rents from living in owner-occupied housing, which raises the shares of net operating surplus and consumption of fixed capital.

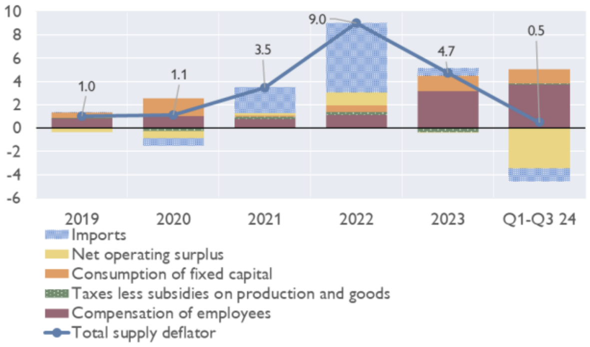
[7] Note that we rely on a definition of "profits" based on national accounts data. First, this implies that we value consumption of fixed capital (or depreciation) at contemporary market prices. Second, net interest payments do not affect our definition of profits (unless they are part of FISIM). Valuing depreciation at the original purchase price of capital goods (as Weber and Wasner, 2023, have argued for) would have led to larger profit contributions in 2022 and 2023, when prices of investment goods rose substantially. At the same time, deducting net interest payments from profits would have led to lower profits (or even stronger negative contributions) from 2022 to 2024, particularly in 2023.

[8] Our results for 2019 to 2023 are based on very detailed data from the annual accounts. However, the numbers for 2024 have been computed using preliminary data from the quarterly accounts, which may change substantially until the release of the annual accounts for 2024 in autumn 2025. This uncertainty particularly concerns the level and composition of profit growth.

Chart 3.3

Inflation decomposition for Austria: total supply deflator

Annual change in % (value-added deflator), contributions in percentage points

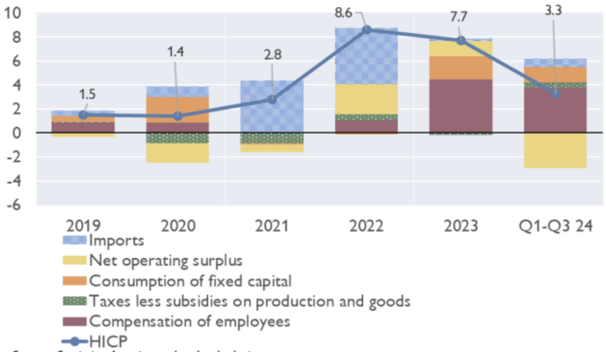


Source: Statistics Austria, authors' calculations.

Chart 3.4

Inflation decomposition for Austria: HICP

Annual change in % (HICP), contributions to inflation in percentage points



Source: Statistics Austria, authors' calculations.

The difference between the GDP and value-added deflator versus the HICP has been striking over the last years. In 2021 and particularly in 2022, the HICP increased much more strongly than the GDP deflator (chart 3). The main reason is the large increase in import prices, which had no direct effect on the GDP deflator, but a very large one on HICP (as well as on the total supply deflator). If we look at the period from 2020 to 2022, the total supply deflator behaves relatively similar to the HICP, but in 2023 and 2024 it is far below it. In those years, both the investment and the export deflator (not shown in charts 3.1 to 3.4) increased much less than the HICP as unit cost increases were particularly strong in consumption-intensive services industries (restaurants and hotels, real estate etc.). The latter effect also impacts the differential between the HICP and the GDP deflator in 2023/24, but this is broadly compensated by the HICP-dampening effect of weak or even negative growth in import prices in those years.

These developments also contribute to the remarkable results concerning the relative role of profits and wages for the HICP and the GDP deflator. In the two years with the highest inflation rates, namely 2022 and 2023, the contribution of wages to the HICP was lower than that to the GDP deflator, while the opposite was the case for profits. The strong recovery of the aforementioned consumer services industries led to a pickup in profits that had a much higher impact on the HICP than on the GDP deflator. At the same time, the drop in profits in manufacturing affected the GDP deflator more strongly than the HICP. This trend also continued in the first three quarters of 2024, when HICP inflation was comparatively lower.

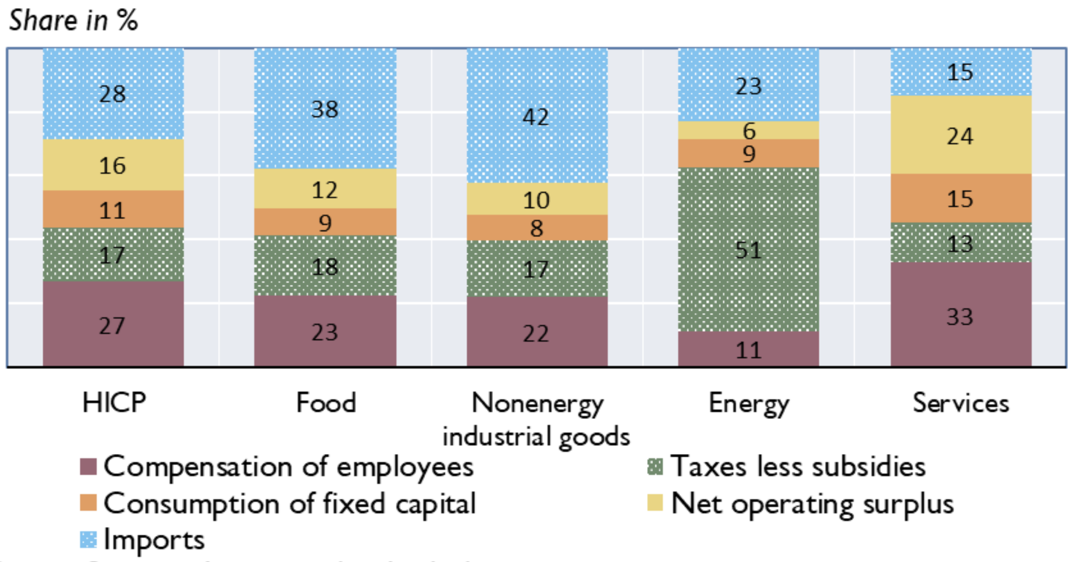
3 Detailed results for HICP special aggregates and the role of profits

To get a better understanding of the differences of HICP inflation versus other price variables, it is also helpful to look at the four main special aggregates of the HICP, namely food, energy, nonenergy industrial goods, and services. These categories differ substantially in their cost structure (chart 4). In 2019, about half of spending on energy was on taxes (mostly mineral oil tax, energy taxes and VAT), while for the other categories it was below one-fifth. The share of imports is highest for nonenergy industrial goods and food. Accordingly, the combined share of wages and profits is highest for services and lowest for energy. In 2019, the ratio of wages to profits was around 2:1 for energy, nonenergy industrial goods and food, while it was only around 4:3 for services.[9] For overall GDP it was around 5:2.

[9] Note that our method takes into account subsequent changes in the share of profits. This is particularly relevant for energy as profits of energy producers were particularly volatile.

Chart 4

Cost shares of headline HICP and special aggregates for Austria (2019)



Source: Statistics Austria, authors' calculations.

3.1 Consumption components with higher import weights showed faster increases in inflation

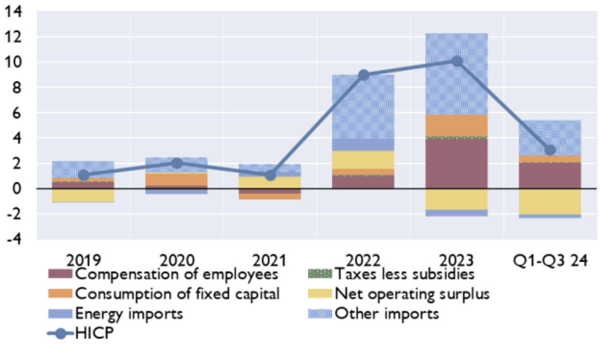
The initial increase in inflation in the second half of 2021 could be primarily attributed to imports (section 2). Initially, this primarily affected nonenergy industrial goods and energy, amid the partial recovery of from the COVID-19 crisis and worldwide shortages in the production of durable goods (e.g. cars). In early 2022, prices for food imports also picked up amid the Russian attack on Ukraine. Services were only marginally impacted by increases in import prices.

Profits of domestic energy producers increased substantially in 2022 and 2023, while at the same time various fiscal measures (energy tax cuts, subsidy on electricity consumption) dampened energy inflation. Interestingly, a large share of households' contracts for heating energy and electricity involves price fixing, leading to a lagged pass-through of wholesale prices to consumer prices in Austria. Therefore, profits of energy producers continued to rise significantly in 2023 when prices of energy imports dropped, and energy inflation went down substantially. Only in the first three quarters of 2024, these profits started to decline.

Chart 5.1

Decomposition of HICP special aggregates: Food

Annual change in % (HICP), contributions in percentage points



Source: Statistics Austria, authors' calculations.

Chart 5.2

Decomposition of HICP special aggregates: Nonenergy industrial goods

Annual change in % (HICP), contributions in percentage points

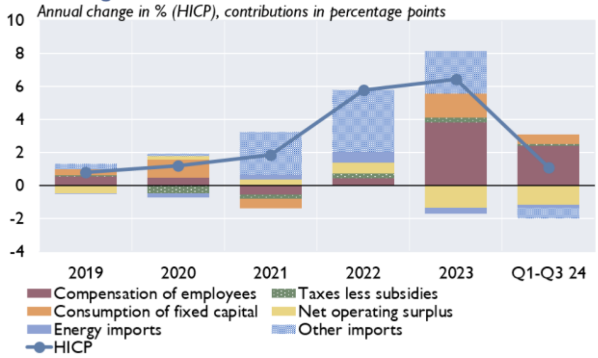
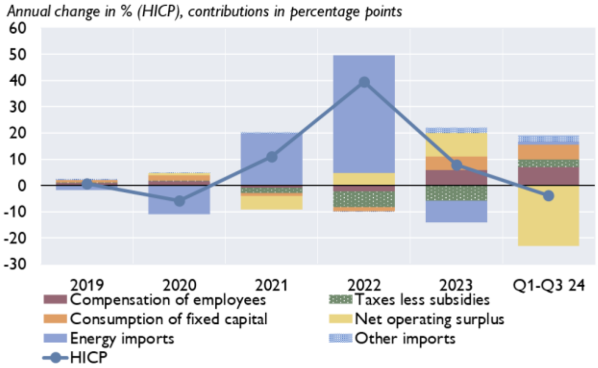


Chart 5.3

Decomposition of HICP special aggregates: Energy

Annual change in % (HICP), contributions in percentage points

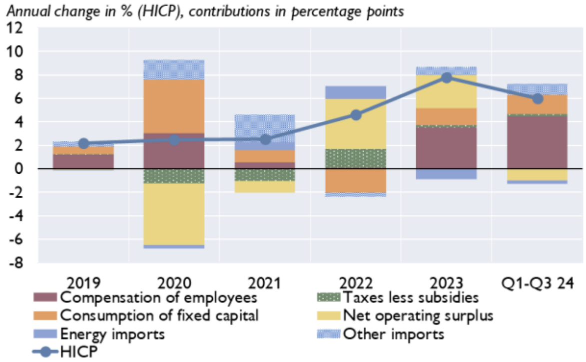


Source: Statistics Austria, authors' calculations.

Chart 5.4

Decomposition of HICP special aggregates: Services

Annual change in % (HICP), contributions in percentage points



The increase in both food and nonenergy industrial goods inflation in 2022 was also accompanied by increases in domestic profits. These additional profits were primarily observed in the trade sector. In 2023, wages increased substantially and inflation declined somewhat in these categories, leading to a reversal of profits. Services inflation increased later than the other three main special aggregates. At the same time, its growth rate was above average in 2023, and in the first three quarters of 2024, services were the item with the by far highest inflation rate. As services are more important for the HICP than for other demand aggregates (chart 2), they contribute substantially to the differential of HICP inflation versus the growth in the total supply deflator (chart 3). There are two main reasons why services inflation has been so high compared to the other special aggregates recently: Services have a relatively high wage intensity by comparison, and nominal wage growth was very high in 2023/24. Furthermore, while overall profits have developed very poorly since 2023, the profits of some specific services sectors have jumped, for example for restaurants and hotels, as well as real estate and financial services.

3.2 Profits increased strongly in 2022, but cratered afterward

When inflation rates peaked in 2022, excessive profit growth was deemed one partial cause (Fritzer et al., 2023, Weber and Wasner, 2023). Indeed, profits increased substantially more than other cost components in 2022. This is illustrated in chart 6.1, which compares the actual development of the profit contribution (red line) to a fictional scenario where the share of all cost components remained constant over time (green bars). In such a scenario, the share of profits in all cost components would remain at its 2019 level of about 16% (yellow bar in chart 1), meaning that the profit contribution would always amount to 16% of HICP growth. In such a case, industry markups would also remain constant. The difference to this hypothetical scenario can be interpreted as excess profits (yellow bars in chart 6). While these excess profits were indeed large and positive in 2022, they were substantially negative in 2020 and the first three quarters of 2024. Therefore, the cumulative effect since 2020 is clearly negative. This holds for practically all branches of the economy. The trade sector had strong profit developments in 2020/21 which unwound afterward. The development for restaurants and hotels was exactly the opposite as very weak developments in 2020/21 were followed by strong profit growth from 2022 onward. The financial sector recorded enormous increases in profits after 2020, but the weight of financial services in the HICP is very low (also due to the exclusion of FISIM from the consumption basket). Profits in the energy sector increased dramatically in 2022 and 2023 but dropped considerably in the first three quarters of 2024.

Chart 6.1

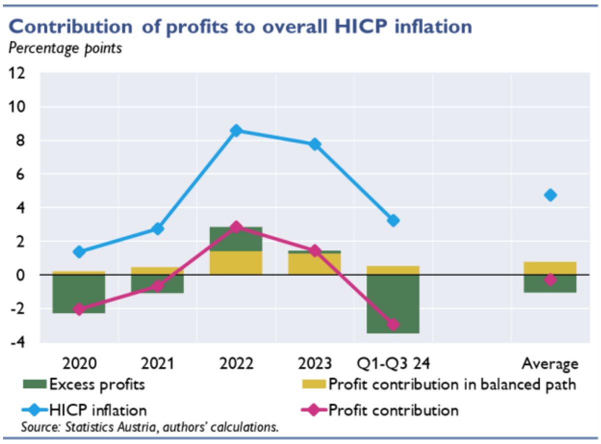
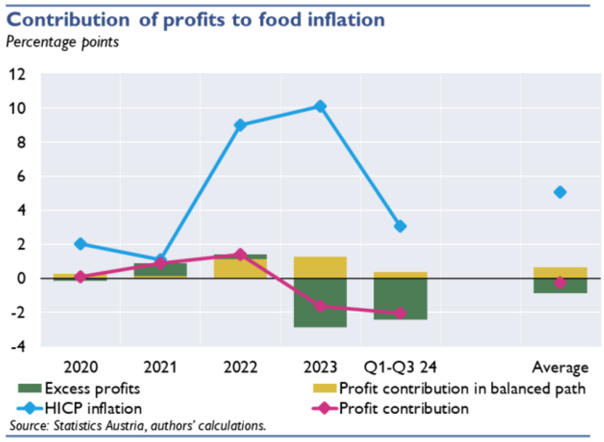


Chart 6.2



One particularly interesting special aggregate in this context is food. Experts at the Austrian Federal Competition Authority (Bundeswettbewerbsbehörde, 2023) were tasked with investigating whether increased profit margins contributed to the high food inflation in Austria. They found no evidence of increases in the profit margins of food producers and retailers in 2022 and the first half of 2023, measuring profit margins as the share of profits in revenue. Our study is consistent with their results. Overall excess profits related to food consumption were rather small in 2022 and substantially negative in 2023 and the first three quarters of 2024 (chart 6.2). The cumulative effect has been clearly negative since 2019. This is also true for the three main branches involved in the supply of food consumption, namely agriculture, manufacturing and trade. Temporary initial gains made by agriculture (2021/22) and trade (2020/21) were more than neutralized by unfavorable developments in 2023/24.

4 Conclusions

In this paper, we compare cost-based decompositions of the value-added deflator, the GDP deflator and the total supply deflator with the HICP decomposition proposed by Schneider (2024). Our main finding is that decomposing national accounts deflators as a proxy for consumer price inflation can lead to misleading results. This is mainly attributable to the different roles of imports and wages. During the last years, rises in import prices were the main contributor to the initial rise in Austrian consumer price inflation. The role of wages was less important for the HICP than for the GDP deflator. Domestic wages made up only slightly more than a quarter of the costs incurred for the production of domestic consumption goods and services, while they were more important for domestic value added. Domestic profits, on the other hand, had a higher impact on the HICP than on the GDP deflator in the period with the highest inflation rates due to the recovery of the consumer services sectors.

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Annex

This annex details the HICP decomposition based on Schneider (2024). It combines the cost structure of the consumption bundle underlying the HIPC derived from the input-output table with quarterly national accounts and trade data. The method involves calculating cost shares at the CPA-74 level, aggregating them to COICOP-45 level, and updating these cost shares with quarterly national accounts and trade data.

In the first main part, we use the input-output table for Austria (2019) with 74 goods/industries to calculate the cost components of the consumption bundle underlying the HICP. For each good i, direct and indirect cost components are distinguished. Direct cost components include direct imports and taxes less subsidies on products. They are obtained directly from the input-output table. Indirect cost components are determined by the domestic production of consumption goods. A multiplier analysis is used to derive the indirect cost component k in industry j attributable to the production of consumption good i at the CPA-74 level. This is done by multiplying a final demand vector D_i[10] with the Leontief inverse $((I-A)^{-1})$[11], which gives the vector of output Q_i generated in all industries by the production of D_i.

$$Q_i = (I-A)^{-1}D_i$$

The cost component k of industry j necessary to produce consumption good i is derived by multiplying output of industry j generated by the production of consumer good i $(q_{j,i})$ with the share of cost component k $(cc_{k,j}^{IO})$ in output of industry j $(q_{j,i})$ from the input-output table:

$$cc_{k,j,i}^{CPA} = \frac{cc_{k,j}^{IO}}{q_j} q_{j,i}$$

These cost components must be aggregated from the CPA-74 level to the COICOP-45 level. This is done by utilizing a correspondence table provided by Statistics Austria that maps CPA-74 goods to COICOP-45 categories[12].

In the second main part, the cost shares derived input-output tables are combined with quarterly national accounts data. This is done in five steps. The first step is to estimate the cost components that are missing in quarterly national accounts (QNA). The published QNA data only contain value added and compensation of employees per industry. Therefore, we must estimate the three missing components (net taxes on production, consumption of fixed capital and net operating surplus), which are all published only at the total economy level. Details of this procedure can be found in Fritzer et al. (2023).

In the second step, we adjust compensation of employees, profits and net other taxes on production for crisis-related subsidies. From 2020 to 2022, the Austrian federal government paid out substantial subsidies to firms for short-time work, foregone revenue and increases in energy costs. These transfers led to a strong drop in net indirect taxes and pushed up compensation of employees (short-time work subsidies) and net operating surplus (other subsidies). We have

[10] For each good i, we set the final demand vector D_i to zero except for good i, which we set to the value of private consumption at basic prices from the input-output table.

[11] A is the matrix of technology coefficients which can be obtained by dividing the matrix of intermediate demand by output by industry.

[12] This table has to be converted from purchasing prices to basic prices to account for trade and transport margins (see Schneider, 2024).

adjusted these time series by subtracting the crisis subsidies from them. For a detailed description of these calculations, see Fritzer et al. (2023).

In the third step, we have to address the problem that industry-specific cost components in quarterly national accounts correspond to the production of all final demand components. Hence, we have to isolate the share of the cost components implied by private consumption from other final uses. We do this by performing a multiplier analysis for all 11 final demand components from QNA to obtain their cost shares. Combining these cost shares with final demand from quarterly national accounts, we obtain *hypothetical cost components* implied by each final demand component. We then calculate the share of private consumption for each cost component and refer to is to as "consumption-implied cost component" ($cc_{k,\mathrm{C},t}^{QNA}$). For further details see Schneider (2024).

The fourth step is to combine the cost components derived from the input-output table with growth rates of the consumption-implied cost components at the quarterly level relative to the corresponding quarter of 2019 (base year of our input-output table). This gives us the cost share $cs_{k,i,t}$ for cost component *k* for consumer good *i* in period *t*.

$$cs_{k,i,t} = cs_{k,i}^{IO45} * \frac{cc_{k,\mathrm{C},t}^{QNA}}{cc_{k,\mathrm{C},2019}^{QNA}}$$

In the final step, we use these cost components to calculate inflation contributions. We first have to calculate nominal private consumption of good *i* (which is not available in quarterly national accounts) as the sum of its cost shares.

$$c_{i,t} = \sum_{k=1}^{K} cs_{k,\mathrm{i},t}$$

Then we divide it by the consumer price index to obtain real consumption of good *i*.

$$c_{i,t}^{r} = \frac{c_{i,t}}{p_{i,t}}$$

After this, we calculate unit cost shares (per real unit of consumption good *i*).

$$ucs_{k,\mathrm{i},t} = cs_{k,\mathrm{i},t}/c_{i,t}^{r}$$

Finally, we obtain contributions to year-on-year inflation using the same decomposition formulas as used for value-added deflator.

$$\frac{dp_{i,t}}{p_{i,t-4}} = \sum_{k=1}^{K} \frac{ducs_{k,\mathrm{i},t}}{ucs_{k,\mathrm{i},t-4}} \frac{ucs_{k,\mathrm{i},t-4}}{p_{i,t-4}}$$

Note that the contribution of taxes on products is not computed via unit cost shares but by comparing the HICP to the HICP at constant tax rates.[13]

[13] Subsidies on products are very small in Austria. For energy crisis-related subsidies on products (particularly for the electricity price cap), we computed the contributions to the HICP ourselves using quarterly data on the payouts of these subsidies. In the decompositions of the GDP deflator and the total supply deflator in section 2, we calculate the contribution of net taxes on products as the difference between the GDP deflator and the value-added deflator.

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