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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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De Nederlandsche Bank NV
P.O. Box 98
1000 AB AMSTERDAM
The Netherlands

Detecting turning points in the inflation cycle

Marco Hoeberichts[a], Jan Willem van den End[a,b]

[a] De Nederlandsche Bank, the Netherlands
[b] Vrije Universiteit Amsterdam, the Netherlands

Abstract

Based on a non-parametric method we construct a leading indicator for turning points in the inflation cycle. We extract the cycle by a band pass filter and identify the turning points by the Bry Boschan algorithm. The selection of variables in the leading indicator is based on turning point matching and dynamic correlation, while the weights are adjusted for cross-correlation between the variables. We apply the method to core inflation in the Netherlands and the euro area. We show that turning points in the core inflation cycle explain inflation forecast errors. Moreover, we show that since the pandemic the cycle of core inflation has mainly been driven by external factors and that the inflation cycle will remain below trend well into 2024.

JEL classification: C82, E31, E37, E58
Keywords: Euro area inflation, Trend-cycle decomposition, Leading indicators, (Turning point) forecasts, Real-time analysis

* Corresponding author. Email address: w.a.van.den.end@dnb.nl
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1. Introduction

The increased uncertainty about inflation dynamics since the Covid-19 pandemic has raised questions about the use of model forecasts for inflation (Lagarde, 2023). The recent large and unprecedented shocks and shifts in economic relationships have reduced the trust in models that are usually based on past regularities. Several ways have been proposed to deal with this. Goodhart (2023) advocates the use of scenarios as a tool to map out the uncertainty around point forecasts of inflation. A related approach is complementing the baseline forecast with sensitivity analyses to provide a richer representation of the inflation outlook (Chahad et al., 2022).

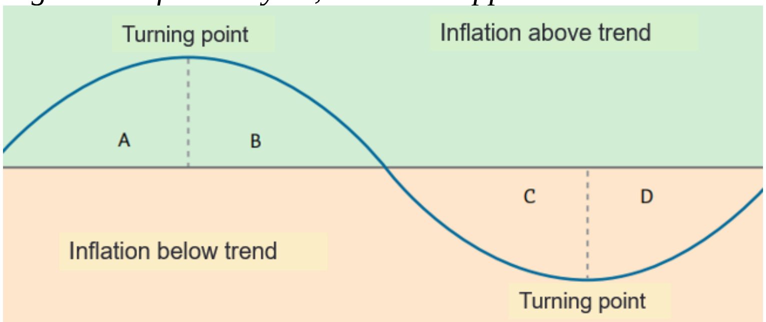
Policy-wise, central banks have adopted a data-dependent approach for their interest rate decisions. A greater reliance on incoming economic and financial data would be appropriate in an environment of elevated uncertainty in which model forecasts are more prone to errors (Lagarde, 2023). However, a potential drawback of data dependency is that policymaking becomes more reliant on backward looking information. Hence, a data dependent approach requires variables that embed forward looking information about inflation. Such information can be combined in a composite leading indicator (CLI), which includes variables with leading properties regarding a reference series like inflation.

CLIs are a common tool in business cycle analysis, as for instance used by the OECD (Gyomai and Guidetti, 2012) and the Conference Board (Levanon et al., 2011). These CLIs are used to predict switches between expansion and recession phases of the economy up to several months ahead, before they are apparent in GDP growth data. CLIs for inflation are less common. De Bondt et al. (2021) develop a CLI for inflation in the euro area, building on previous approaches. Since CLIs are mainly used to predict turning points in the cycle of the reference series and not to forecast future GDP growth or inflation, they complement forecasting models. Such model tend to be less accurate at cyclical turning points associated with a recession or a strong boom (An et al., 2018) and so the ability of CLIs to predict turning points has added value particularly at inflection points of macro-economic cycles.

CLIs date the turning points in the cycle by non-parametric approaches based on pattern recognition algorithms. These are non-parametric in the sense that they do not require the estimation of model parameters. It makes them less prone to model risk, which is particularly advantageous in an environment of high uncertainty. Parametric approaches do estimate the probability of switching from one regime to another, like Markov switching models that estimate the likelihood of recession and expansion regimes. Aviat et al. (2021) state that turning point dating based on parametric models present a larger variance across models than those obtained through non-parametric approaches, which they relate to the sensitivity of parametric approaches to model risk. Moreover, they find that non-parametric approaches, like CLIs, are simple and effective in dating cyclical turning points.

Two approaches can be applied to describe the cycle by CLIs: the classical approach and the deviation approach. The former considers the fluctuations of the level of economic activity, as measured by GDP growth rates, while the latter considers the cyclical fluctuations around the trend. The detrending procedure produces a stationary cyclical component. The level of the cycle in the deviation approach has a different meaning than the level of growth rates in the classical approach. In the stylized example of Figure 1 for instance, the normalized inflation cycle above the horizontal axis (i.e. the normalized inflation trend) implies that inflation is above trend and vice versa for the cycle below the horizontal axis.

Figure 1. Inflation cycle, deviation approach



A (B) → inflation above trend and increasing (decreasing)
C (D) → inflation below trend and decreasing (increasing)

Stylised representation of deviation approach for the inflation cycle.

In this paper, we construct a CLI for the inflation cycle in the euro area and the Netherlands based on the deviation approach. This approach relates to the New Keynesian Phillips curve, which explains the deviation of inflation from its steady-state level (the inflation gap) by the deviation of output from its potential (the output gap), amongst other explanators. While central banks also analyse the inflation trend, for instance to assess the persistence of inflation (see for instance Stock and Watson, 2016), monetary policy foremost influences the inflation cycle, through its impact on output. Hence, the Phillips curve and related gap measures for inflation and output are key in monetary policy frameworks (Eser, 2020).

We focus on the cycle in core inflation (CPIX), i.e. inflation excluding energy and food, for several reasons. First, core inflation is less affected by noise stemming from temporary or idiosyncratic factors (Ehrmann et al., 2018). Thereby core, or underlying inflation reflects price developments in the medium term, which is usually the horizon of monetary policy. Second, in an environment characterised by large relative price shocks, it is uncertain to what extent the shock effects are temporary. The persistence of the shock effects and related second round effects are reflected in core inflation. Third, core inflation can also be explained by the Phillips curve (Ball and Mazumder, 2021).

The rest of the paper is structured as follows. Section 2 reviews the related literature on CLIs for inflation. Section 3 summarizes the data we use and section 4 discusses techniques to extract the cycle. In section 5 and 6 we explain the empirical approaches to date the turning points and to construct the CLI. In section 7 we estimate the probability of turning points in the core inflation cycle and in section 8 we apply the turning point indicator to explain inflation forecast errors of structural models. Section 9 presents robustness tests and section 10 concludes.

2. Contribution to the literature

Early papers about turning point indicators for inflation include Moore and Kaish (1983) for the US and Binner et al. (1999, 2005) for the UK and the euro area, respectively and Gibson and Lazaretou (2001) for Greece. Artis et al. (1995) select the indicator variables in CLIs for UK inflation based on criteria as smoothness and irregularity, economic coverage, leading properties and graphical turning point analysis. Similar selection criteria are used by Quinn and Mawdsley (1996) to construct a CLI for inflation in Ireland. Bikker and Kennedy (1999) construct CLIs for inflation in seven EU countries. The most recent study on CLIs for inflation is De Bondt et al. (2021), who construct a turning point indicator for the cycles of euro area headline and core inflation.

Building on De Bondt et al. we construct a turning point indicator for the Netherlands and the euro area. We differ from De Bondt et al. in several ways. First, our selection of indicator variables in the CLI is based on their predictive power for the turning points in inflation, next to their correlation with this reference series. The latter is the main selection criterium of De Bondt et al. Second, we take the first principal components of different groups of variables as indicators in the CLI as an alternative approach. Third, we use rebalanced weights to construct the CLI. The rebalanced weights consider the correlation between the indicator variables and increase the influence of uncorrelated variables which have a unique contribution. This is not accounted for by De Bondt et al., who weight the variables together in the CLI by averaging (i.c. equal weighting scheme).

Fourth, our choice of the data and data transformation differ. We focus on the HICP core inflation measure, excluding energy and food, to eliminate the impact of large swings in these volatile components on the reference series. Another difference is that De Bondt et al. extract the cycle for the year-on-year (y-oy) rate of the HICP measures, while we compute the seasonally adjusted 3 month-on-3 month (3m-3m) change of inflation.[1] Moreover, we apply the analysis to the Netherlands as well as to the euro area. For the Netherlands, longer historical series are available than for the euro area.

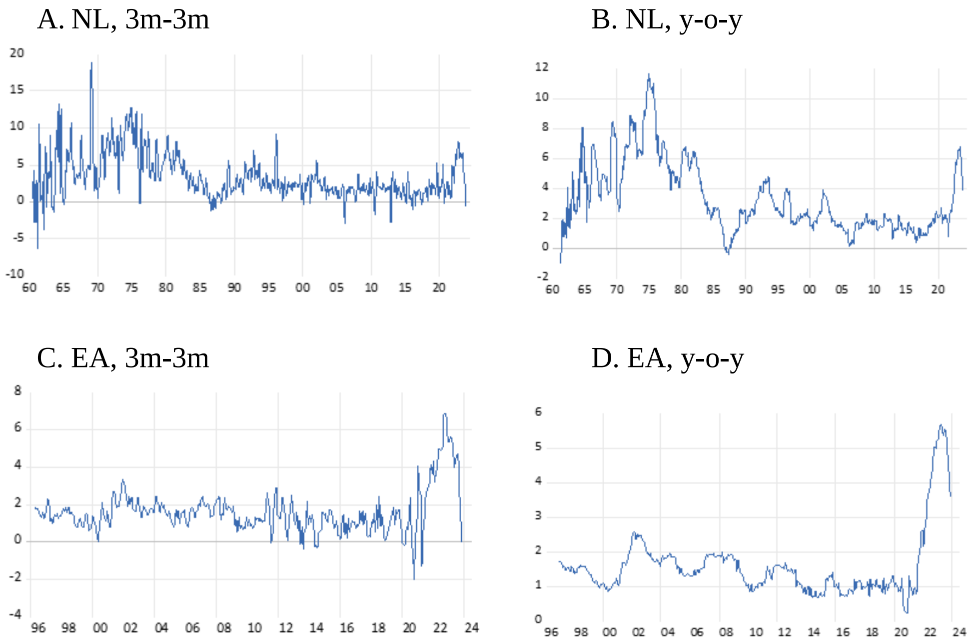
Fifth, we extend the analysis of De Bondt et al. by also estimating probit models for the turning points in core inflation. We estimate a binary probit model for peaks and troughs in the inflation cycle, using the indicator variables as regressors. We also estimate an ordered probit model with the peak, neutral and trough as three stages in the inflation cycle. The probit models provide an estimate for the probability of turning points in the inflation cycle. Finally, we check whether our turning point indicator helps to improve the inflation forecasts that are regularly produced by Eurosystem staff. We assess the forecasts around the turning points in the inflation cycle, by estimating the relationship between past forecast errors and our turning point indicator.

[1] We do not use the month-on-month change due to the high frequency noise in monthly prices.

3. Data

We analyse the turning points in the cycle of core inflation in the euro area (EA) and the Netherlands (NL). This is the reference (benchmark) series for the CLI. For NL the core inflation series is available since 1960 and for the EA since 1996, both on a monthly basis. Figure 2, panels A and C show the annualised 3m-3m percentage changes of CPIX and panels B and D the annual changes (y-o-y), both adjusted for seasonal effects. The 3m-3m changes are more volatile as they reflect more of the transitory price changes. The y-o-y changes to a larger extent include carry-over effects of inflation 12 months ago which influences the current y-o-y inflation rate. This leads to a smoother series and some tendency towards predictability.

Figure 2. Core inflation (CPIX)



Core inflation series (CPIX), transformed into 3m-3m changes (left panels) and y-o-y changes (right panels). NL core inflation is available since 1960m4 and for the EA since 1996m4. The series are seasonally adjusted and the NL series is also adjusted for VAT (value added tax) changes.

The CLI is composed of indicator variables that have potential leading properties for core inflation. We apply two approaches: 1. the individual variable approach and 2. the principal component approach. The first approach comprises a set of 34 variables that are classified in six groups (see Table 1 and Annex 1 for a detailed variable description). The second approach takes the first principal component of each group as variable in the CLI. The first principal component accounts for the maximum possible proportion of the variance of indicator variables in each group.

Table 1. Indicator variables and groups

Groups	***Indicator variables***	***Groups***	***Indicator variables***
Business cycle	Consumer expenditures	**Commodity prices**	Commodity price index non-energy
	Industrial production		Commodity price index energy
	Producer confidence		Oil price
	Consumer confidence		CPI energy
	PMI manufacturing		
	IFO index	**External conditions**	Global supply chain index
	Industry capacity utilization		OECD CPI
	Vacancy indicator		Import prices
			Euro dollar
Prices and costs	PPI final goods prices		
	PPI intermediate goods prices	**Financial**	House price
	PMI sales prices		Long-term nominal interest rate
	PMI purchase prices		Short-term real interest rate
	Wages		Yield spread
			Corporate credit spread
Price expectations	Selling price expectations intermediate goods		Stock index
	Selling price expextations consumer goods		Gold price
	Inflation expectation (Refinitive)		M3
	Inflation expectations (Consensus Economics)		M1

Variables for NL and EA included in the turning point analysis (indicator variable approach) and grouping of the variables (principal component approach).

The six groups of indicator variables cover different segments of the economy and are related to different elements of the Phillips curve. The business cycle group relates to slack, or the output gap, the prices and costs group to marginal costs, price expectations to the forward looking Phillips curve and external conditions and commodity prices to the cost push shock in the Phillips curve. The financial variables relate to the transmission channels of monetary policy. Related studies apply comparable groupings of variables (e.g. De Bondt et al., 2021 and McCracken and Ng, 2016).

The individual variable approach and the principal component approach both have their pros and cons. The advantage of the first approach is that only variables are included that meet the criteria for inclusion in the CLI, though a potential disadvantage is that signals could be missed in variables that are excluded from the CLI. The advantage of the second approach is that a wider information set is included, which also makes the CLI less prone to changes in the economy that may be picked up by specific variables. A disadvantage of the principal component approach however is that also variables are included which individually could have weak leading properties regarding the reference series. However, those variables by construction will get a relatively low loading in the principal component approach, which to some extent addresses this disadvantage.

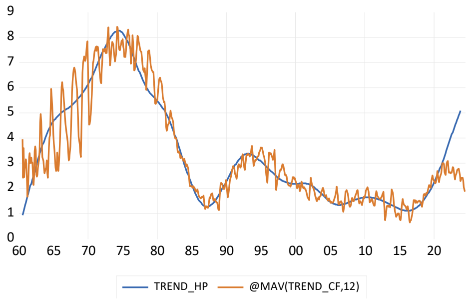
The reference series (CPIX) and the 34 indicator variables are adjusted for seasonal effects and for VAT changes (for Netherlands). The variables are log transformed when appropriate, after we take the 3m-3m or y-o-y changes (see Annex 1). The few series that are only available on a quarterly basis are interpolated to monthly series by a Kalman filter. Subsequently we extract the cycle from each transformed series by the trend-cycle decomposition method described in the next section and then normalize the cycles. For the principal component approach we take the first principal component of the normalized cycles of the variables in each group.

4. Trend-cycle decomposition

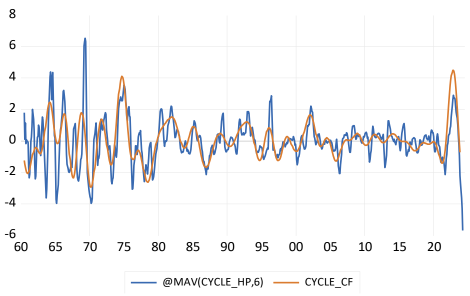
We extract the cycles of the reference series (i.c. core inflation) and the indicator variables by a band-pass filter. Various filters are available to decompose the series in a trend, cyclical and noise (or seasonal) component. The Hodrick-Prescott (HP) filter and Christiano-Fitzgerald (CF) filter are commonly used for the construction of CLIs for the business cycle or inflation. For instance, the OECD applies the HP filter to decompose the business cycle into cyclical and trend growth, while De Bondt et al. use the CF filter to extract the inflation cycle. Applying both filters to 3m-3m core inflation in the EA and NL shows that the filters lead to similar results for the cycle and trend (Figure 3[2]), although the trends diverge at the end of the sample, reflecting the sensitivity to the end-point, as we explain below.

Figure 3. Trend - cycle decomposition CPIX

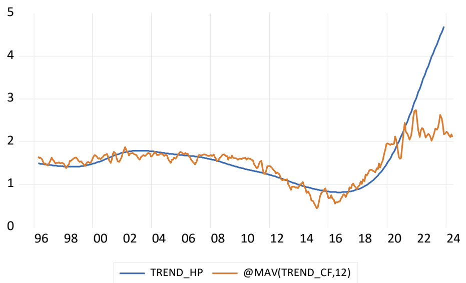
A. Trend HP and CF filters (NL)



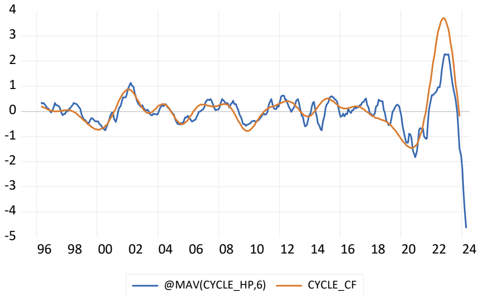
B. Cycle HP and CF filters (NL)



C. Trend HP and CF filters (EA)



D. Cycle HP and CF filters (EA)



Trend (left hand panels) and cycle (right hand panels) of core inflation extracted by Hodrick-Prescott (HP) filter (blue lines) and Christiano-Fidzgerald (CF) filter (red lines), based on 3m-3m changes in core inflation. HP filtered cycles are 6 months moving averages and CF filtered trends are 12 months moving averages.

[2] In Figure 3 we take the moving average of the CF filtered trend and the HP filtered cycle to smooth the influence of the noise term, which is included in the CF filtered trend and in the HP filtered cycle.

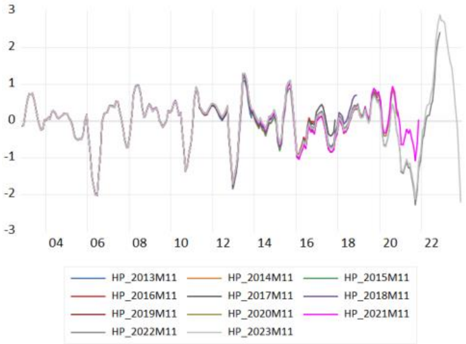
The motivation of De Bondt et al. for using the CF filter is that it works well in real-time applications (in which the end-point problem is an issue) and for economic time series that follow a random walk. According to Mohr (2005), an end-point problem exists if the stochastic model underlying the filter does not represent the data well. This issue can be alleviated by applying the random walk assumption in the CF and HP filters, which fosters that new observations comply with the implicit (random walk) forecast of the filter. Moreover, by applying an asymmetric one-sided filter one does not make future projections and only rely on current and past data.

We apply an asymmetric CF filter to extract the cycle of the core inflation series. The cyclical component is extracted by removing frequencies that are higher than 24 months and lower than 120 months. The 24 month lower band is higher than the lower band set by De Bondt et al., for the reason that we apply the filter to core inflation. This inflation measure is by nature more persistent than headline inflation and thus has longer waves.

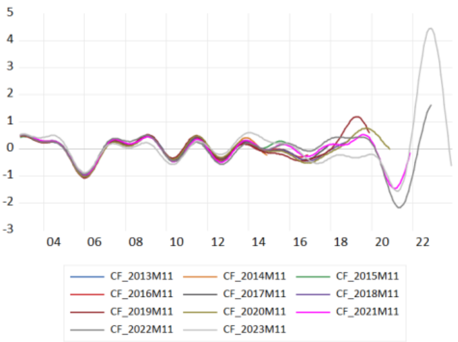
Applying the random walk assumption to an asymmetric filter does not fully address the end-point problem. Figure 4 shows that cycles extracted from older vintages of the core inflation series are associated with end-points that differ from those of cycles extracted from newer vintages. Nonetheless, the cycles do not suffer from serious phase shifts, in the sense that the turning points in the cycles are comparable across the different vintages.

Figure 4. Real time estimates of cyclical component

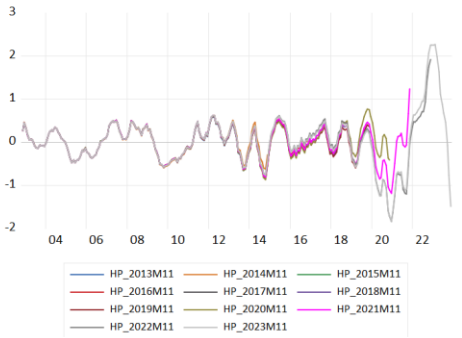
A. Cycle HP filter (NL)



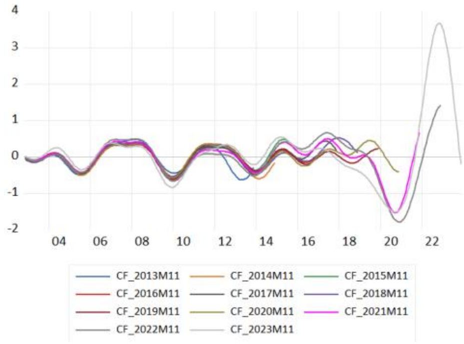
B. Cycle CF filter (NL)



C. Cycle HP filter (EA)



D. Cycle CF filter (EA)



Real time estimates of the cycle in core inflation, extracted by Hodrick-Prescott (HP) filter and Christiano-Fitzgerald (CF) filter, based on 3m-3m changes in core inflation. Each line shows the cycle based on a different vintage of the inflation series. A new vintage is created by adding 12 months to the previous vintage. HP filtered cycles are 6 months moving averages.

5. Selection of indicator variables

To select the indicator variables and set the weights in the CLI, we combine two methods: the Bry-Boschan (BB, 1971) algorithm and dynamic correlation analysis. The BB algorithm identifies the turning points, both in the reference series (CPIX) and the indicator variables (and principal components). This enables the matching between them, which is our main selection criterium for the indicator variables. The correlation analysis measures the co-movement between the reference series and lags of the indicator variables (or their principal components) and is used as second selection criterium and metric for calibrating the CLI weights.

5.1 Turning point dating

The BB algorithm outlined in Harding and Pagan (2002) is a widely used method to date turning points in the business cycle, as for instance by the NBER and OECD. The algorithm applies a systematic approach to identify local minima and maxima in the cycle, based on the following rules:

1. Peaks and troughs should alternate (i.e., two peaks cannot follow each other), implying the ordering $C^T_{t-n},\ C^P_t,\ C^T_{t+n}, \dots$, with C^P the local peak in the cycle, C^T the local trough in month t.
2. There should be at least n^c months between one peak and the next peak (i.e., the minimum duration of a full cycle, composed of an upward phase and a downward phase, must be n^c months).
3. There should be at least n^d months between a peak and a trough (i.e., the minimum duration of a phase in the cycle is defined as n^d months, with $n^d < n^c$).
4. The minimum phase restriction is overruled if the fall in a series is very large, which allows the downward phase to be shorter. The parameter controlling this is called the threshold.

These rules imply that,

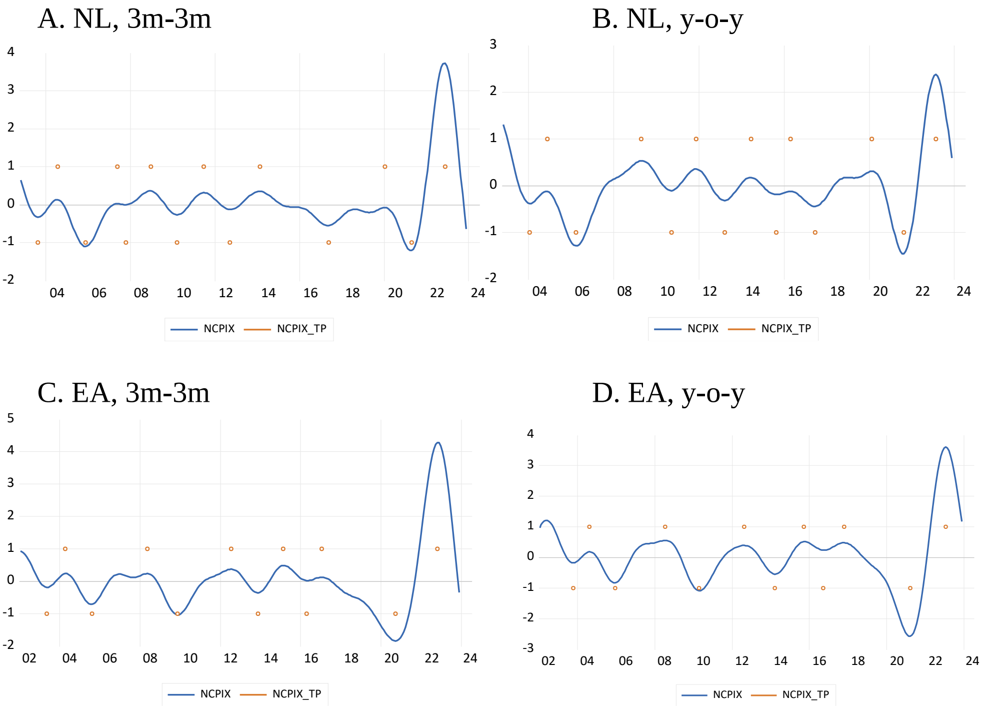
$$C_{t-n^d} < \cdots < C_{t-1} < C^P_t > C_{t+1} > \cdots > C_{t+n^d} \qquad (1)$$

$$C_{t-n^d} > \cdots > C_{t-1} > C^T_t < C_{t+1} < \cdots < C_{t+n^d} \qquad (2)$$

In the business cycle literature, the minimum cycle length n^c is usually set at 15 months and the minimum phase length n^d at 5 months (Bry and Boschan, 1971). To identify the turning points in the cycles of the reference series and indicator values for core inflation in EA and NL we set $n^d = 5$ and $n^c = 18$. The latter value is chosen to avoid that small blips in the cycle of the reference series are dated as turning points (a higher n^c means that only more pronounced turning points are identified).

Figure 5 shows the cycle and the identified turning points for the reference series CPIX in EA and NL. Between 2002m1 and 2023m11 the algorithm dates 14 turning points in NL and 12 in EA. On average, the turning points are detected 4 months earlier for the cycle based on 3m-3m changes of inflation compared to y-o-y changes. This is a main reason for us to construct the benchmark CLI based on the 3m-3m changes in core inflation.

Figure 5. Turning points in CPIX cycle



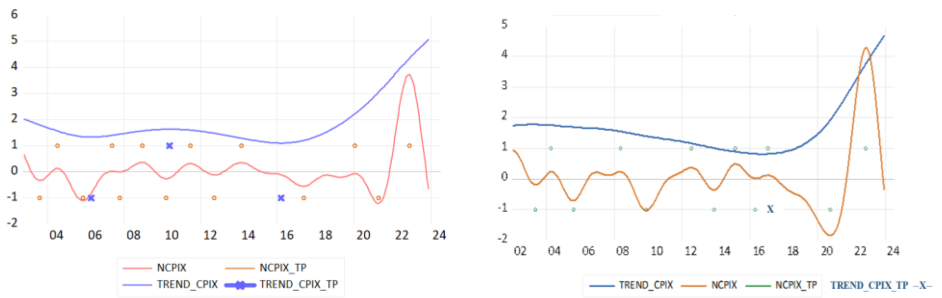
Core inflation cycle (NCPIX) and turning points in the core inflation cycle (NCPIX_TP, represented by the dots). Based on 3m-3m changes (left-hand panels) and y-o-y changes (right-hand panels).

A relationship between turning points in the cycle and in the trend of the reference series is not obvious (Figure 6[3]). The BB algorithm identifies a few turning points in the trend and in most cases these do not match with the turning points in the cycle. The loose relationship between turning points in the trend and the cycle follows by construction from the band-pass filter, which eliminates the trend component for extracting the cycle and vice versa.

[3] The cycle is extracted by the CF filter and the trend by the HP filter, since the latter extracts a pure trend, while the trend extracted by CF filter includes the noise component in the trend.

Figure 6. Turning points in the CPIX cycle and trend

A. NL B. EA



Core inflation cycle (NCPIX) and turning points in the core inflation cycle (NCPIX_TP, represented by the dots). Trend in core inflation (TREND_CPIX) and turning points in the inflation trend (TREND_CPIX_TP, represented by the crosses). Based on 3m-3m changes.

After having dated the turning points in the reference series and the indicator variables, the next step is to match both. The matching is used to select the indicator variables for the CLI. We use the selection criterium that at least 60% of all turning points in the reference cycle is preceded by a turning point in the indicator variable cycle, with a minimum average lead time of 6 months and a maximum average lead time of 18 months ($6 \leq n \leq 18$). The 60% threshold is chosen to roughly balance between selecting a sufficient number of variables for inclusion in the CLI and finding indicators of which the turning points precede more than half of the turning points in the reference series. Table 2 shows that 12 out of 34 variables meet this criterium for NL and 5 for EA. House prices and non-energy commodity prices meet the criterium in both the EA and NL.

Table 2. Results turning point matching: by indicator variable

A. NL

Indicator	TP detected	Lead time (mean)	Indicator	TP detected	Lead time (mean)
Selling price exp interm goods	86%	12	OECD CPI	50%	11
Global supply chain index	79%	12	Commodity prices energy	50%	15
Selling price exp cons goods	71%	12	Industrial production	50%	14
Commodity prices non-energy	71%	15	PMI purchase prices	50%	12
PPI final goods prices	64%	11	Vacancy indicator	50%	15
Import prices	64%	12	Consumer confidence	50%	12
Consumer expenditures	64%	14	CPI energy	43%	11
Inflation exp (Refinitive)	64%	15	PMI NEVI	43%	14
Producer confidence	64%	13	IFO index	43%	13
House price	64%	12	Oil price	43%	16
Long-term nom interest rate	64%	8	Wages	43%	12
Gold price	64%	12	Industry capacity utilization	36%	13
Inflation exp (Consensus)	57%	11	Corporate credit spread	36%	11
PPI intermediate goods prices	57%	12	M3	29%	11
Yield spread	57%	9	M1	29%	9
Stock index	57%	16	Short-term interest rate (real)	21%	11
PMI sales prices	50%	14	Euro dollar	21%	14

B. EA

Indicator	TP detected	Lead time (mean)	Indicator	TP detected	Lead time (mean)
OECD CPI	83%	10	PMI sales prices	42%	11
Commodity prices non-energy	75%	10	Selling price exp interm goods	42%	11
House price	67%	11	Industry capacity utilization	42%	8
CPI energy	67%	11	Inflation exp (Refinitive)	42%	11
Oil price	67%	13	Import prices	33%	8
Vacancy indicator	58%	11	Global supply chain index	33%	8
Consumer expenditures	58%	10	Producer confidence	33%	12
Commodity prices energy	58%	10	PMI purchase prices	33%	11
Industrial production	58%	10	Long-term nom interest rate	33%	16
Euro dollar	58%	14	Stock index	33%	12
Inflation exp (Consensus)	50%	8	PPI intermediate goods prices	25%	8
PMI NEVI	50%	11	Short-term interest rate (real)	25%	15
IFO index	50%	12	M1	25%	15
Gold price	50%	7	Wages	17%	12
Yield spread	50%	11	Consumer confidence	17%	9
PPI final goods prices	42%	9	M3	17%	11
Selling price exp cons goods	42%	12	Corporate credit spread	8%	17

Results turning point matching, based on indicator variable approach. TP detected is the percentage of turning points in the core inflation cycle that is preceded by a turning point in the variable, within a horizon of 6 – 18 months. Lead time is the average period (in months) between the date of the turning point in the inflation cycle and in the turning point of the cycle of the variable.

Regarding the principal components of each group of indicator variables, only one principal component meets the 60% matching criterium, being the price expectations component in NL and the commodity price component in EA (Table 3). Since we include all six components in the CLI based on the principal component approach, the turning point matching criterium is actually not used as a selection criterium in that approach.

Table 3. Results turning point matching: by principal component

A. NL

Indicator (component)	TP detected	Lead time (mean)
Price expectations	79%	14
External conditions	57%	15
Commodity prices	57%	11
Prices and costs	43%	14
Business cycle	36%	12
Financial	36%	11

B. EA

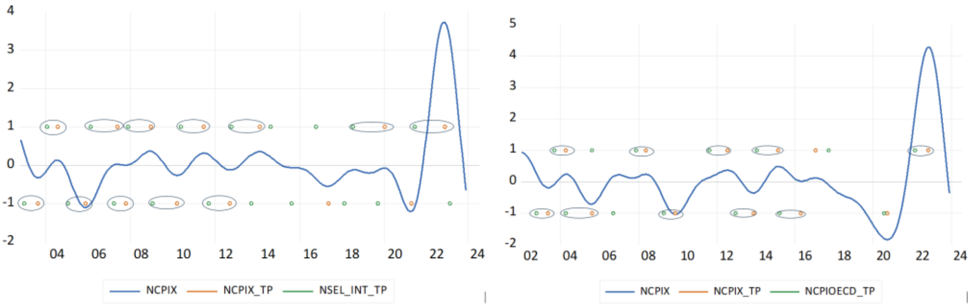
Indicator (component)	TP detected	Lead time (mean)
Commodity prices	75%	11
Prices and costs	50%	9
Price expectations	50%	9
Business cycle	33%	10
Financial	33%	13
External conditions	17%	9

Results turning point matching, based on principal component approach. TP detected is the percentage of turning points in the core inflation cycle that is preceded by a turning point in the cycle of the principal component, within a horizon of 6 – 18 months. Lead time is the average period (in months) between the date of the turning point in the inflation cycle and in the turning point of the cycle of the principal component.

Figure 7 shows how well the turning points in the reference series match with the best performing indicator variable. The circles connecting both turning points are drawn for cases that meet the lead time ($6 \leq n \leq 18$) and matching criterium (>60%). The best performing indicator variable for NL (selling price expectations of intermediate goods[4]) detects 86% of all turning points in the CPIX cycle with a minimum lead time of 6 months, while for EA this is the case for global inflation (OECD CPI[5]) in 83% of the CPIX turning points.

Figure 7. Turning point matching of best indicator variable

A. NL B. EA



Core inflation cycle (NCPIX); turning points in the inflation cycle (NCPIX_TP, red dots) and turning points in the cycle of the indicator variables (green dots) that have the highest match with the turning points in inflation cycle, i.c. SEL_INT_TP for NL and NCPIOECD_TP for EA. Based on 3m-3m changes.

[4] The variable *Selling price expectations of intermediate goods* is highly correlated with variable *Selling price expectations of consumer goods*. The rebalanced weighting scheme, explained in section 6.1, takes this into account, by adjusting the weights of the variables in the CLI to avoid statistical double counting.

[5] While euro area inflation is part of OECD inflation, the latter has leading properties for euro area core inflation (NCPIX) and is therefore useful to include in the CLI for euro area NCPIX.

5.2 Correlation analysis

The second criterium for selecting the indicator variables is their correlation with the reference series. Related studies also apply this criterium (e.g. De Bondt et al., 2021; Gyomai and Guidetti, 2012). The correlation coefficient is derived by a dynamic correlation analysis which determines the maximum correlation between lags of cycle C^i of each indicator variable i (or principal component i) and the reference cycle C^r. As selection criterium we impose that the absolute correlation coefficient should be at least 0.5 with a minimum lead time of 6 months and a maximum lead time of 18 months,

$$\max_{6 \leq n \leq 18} \left| Corr\left(C_t^r, C_{t-n}^i\right)\right| \geq 0.5 \qquad (3)$$

Table 4 shows the outcome of the correlation analysis. For NL there are 4 indicator variables (in the red boxes) that do not meet the correlation criterium, while they do meet the turning point matching criterium. Since both criteria must be met, these 4 variables are not included in the CLI. For EA there is only 1 indicator variable (oil price) which does not meet the correlation criterium, while meeting the turning point criterium. Regarding the correlation between the CPIX cycle and lags of the principal component of each group of indicator variables, the correlation criterium is met in almost all instances (Table 5). We note that the risk of spurious correlation in our approach is mitigated since the trend and seasonal components are removed before the series are included in the correlation analysis.

Table 4. Results dynamic correlation, by indicator variable

A. NL

Indicator	Correl max	Lead time
CPI energy	0.88	8
Selling price exp cons goods	0.82	13
Inflation exp (Consensus)	0.82	9
Global supply chain index	0.80	1
PPI final goods prices	0.77	11
Import prices	0.77	12
Short-term interest rate (real)	0.73	12
Consumer expenditures	0.72	12
PPI intermediate goods prices	0.72	13
PMI sales prices	0.70	17
OECD CPI	0.68	9
Commodity prices energy	0.66	15
Industrial production	0.65	14
Industry capacity utilization	0.60	18
Selling price exp interm goods	0.59	16
Inflation exp (Refinitive)	0.58	1
PMI purchase prices	0.56	1

Indicator	Correl max	Lead time
Producer confidence	0.55	18
House price	0.55	16
PMI NEVI	0.53	2
Corporate credit spread	0.52	2
Commodity prices non-energy	0.51	17
Long-term nom interest rate	0.51	5
IFO index	0.49	5
Oil price	0.48	17
Vacancy indicator	0.41	17
Consumer confidence	0.41	4
Wages	0.33	18
Gold price	0.28	18
M3	0.27	9
Yield spread	0.26	11
M1	0.26	12
Stock index	0.25	18
Euro dollar	0.21	10

B. EA

Indicator	Correl max	Lead time	Indicator	Correl max	Lead time
Inflation exp (Consensus)	0.90	8	Industry capacity utilization	0.55	15
PPI intermediate goods prices	0.86	10	M1	0.55	18
Vacancy indicator	0.85	13	Corporate credit spread	0.54	1
Consumer expenditures	0.81	9	Commodity prices non-energy	0.53	16
Import prices	0.81	11	PMI purchase prices	0.50	18
PPI final goods prices	0.79	9	CPI energy	0.50	11
House price	0.79	12	PMI manufacturing	0.49	18
Selling price exp cons goods	0.77	13	Inflation exp (Refinitive)	0.45	13
OECD CPI	0.75	7	IFO index	0.45	2
Global supply chain index	0.75	1	Oil price	0.43	14
PMI sales prices	0.74	17	Long-term nom interest rate	0.39	4
Wages	0.66	2	Consumer confidence	0.36	18
Selling price exp interm goods	0.64	18	M3	0.33	18
Commodity prices energy	0.63	13	Gold price	0.27	17
Short-term interest rate (real)	0.63	11	Stock index	0.26	18
Industrial production	0.58	14	Euro dollar	0.19	6
Producer confidence	0.57	18	Yield spread	0.19	1

Result dynamic correlation based on indicator variable approach. Correl max is the maximum absolute correlation between lags of cycle of each variable and the cycles of the reference series, within a window of 6 – 18 months. Lead time is the lag (in months) at which the absolute correlation coefficient peaks. Variables in the green boxes meet both the turning point matching criterium and the correlation criterium, while variables in the red boxes do not meet the correlation criterium, while they do meet the turning point matching criterium.

Table 5. Results dynamic correlation, by principal component

A. NL

Indicator (component)	Correl max	Lead time
External conditions	0.74	10
Price expectations	0.71	14
Prices and costs	0.69	16
Commodity prices	0.65	14
Business cycle	0.54	18
Financial	0.38	13

B. EA

Indicator (component)	Correl max	Lead time
Prices and costs	0.79	13
External conditions	0.75	9
Price expectations	0.74	13
Business cycle	0.66	17
Commodity prices	0.56	13
Financial	0.52	15

Result dynamic correlation based on principal components approach. Correl max is the maximum absolute correlation between lags of cycle of each principal component and the cycles of the reference series, within a window of 6 – 18 months. Lead time is the lag (in months) at which the absolute correlation coefficient peaks. The components in the green boxes meet the correlation criterium.

The differences between the selected indicator variables for NL and the EA reflect that the core inflation cycles in both regions are driven by different factors. In NL these factors include selling price expectations and pipeline pressures in the production chain that are not primarily related to energy. In the EA, energy prices seem to be a more important determinant of the core inflation cycle. The house price is selected in both regions as an important indicator variable, while other financial variables are not selected for the CLI in both NL and the EA. This indicates that the core inflation cycle is foremost driven by real economic factors, including price expectations, and much less by financial factors.

6. CLI for core inflation

6.1 Rebalanced weights

In this section we weight the selected indicator variables $1 \ldots v$ (first approach) and the principal components $1 \ldots p$ (second approach) to construct the CLI. The literature proposes several weighting schemes and there is no consensus about the preferred scheme (see for an overview Nardo et al., 2005). In many CLIs the indicator variables are given equal weights, assuming that the individual variables are equally important. However, ignoring the importance of underlying relationships leads to bias if indicator variables are related. Another disadvantage of fixed, equal weights is that they do not reflect the time-varying relative influence of indicator variables on the reference series. Alternative methods tend to apply different weights that reflect the economic significance of the indicator variables, their statistical adequacy, cyclical conformity, or timeliness of the available data.

Nardo et al. (2005) show that different weighting techniques can be applied, based on statistical models (e.g. factor analysis, data envelopment analysis, principal components, unobserved components models), or participatory methods (e.g. budget allocation, analytic hierarchy processes). A much used statistical method is to determine the weights by the correlation of the indicator variables with the reference series. This allows for time-varying weights when the correlations, together with the CLI, are regularly updated. A drawback of this approach is ‘statistical double counting’, which occurs when two or more indicators are correlated. To overcome this, the weights should be adjusted, for instance by giving more weight to uncorrelated indicators. We apply this technique of rebalanced weights to construct the CLI of core inflation, whereby the weights are based on the maximum absolute correlation between the reference series and the indicator variables; $\max_{6 \le n \le 18} \left| Corr\left(C_t^r, C_{t-n}^i\right)\right|$.

We tried three different weighting schemes: i) equal weights; ii) weights based on the loadings of the principal component of the indicator variables and iii) rebalanced weights. In the principal component scheme, the CLI is composed by the first principal component of the (lagged) indicator variables. Principal component analysis avoids statistical double counting, but a disadvantage is the loss of information that is not captured by the first component. In section 6.2 we show that the CLI based on equal weights and principal component analysis leads to lower correlation with the reference series than the CLI based on rebalanced weights. For these reasons, our preferred weighting scheme is rebalanced weights. Here we follow Xu and Gertner (2008) who decompose the correlation in two parts,

$$Corr\left(C_t^r, C_{t-n}^i\right) = Corr^c + Corr^u \qquad (4)$$

where $Corr^c$ is the correlated contribution (i.e. variations of an indicator variable (or principal component of a group) which are correlated with other indicator variables (or principal component of other groups). $Corr^u$ is the uncorrelated contribution (i.e. the unique variations of an indicator variable (or principal component of a group) which cannot be explained by any other indicator variable (or principal component of another group). To obtain the two components of the correlation, Becker et al. (2017) propose a regression approach where each indicator variable C_t^i is regressed on the other indicator variables,

$$C_t^{i,1} = \phi_1 + \phi_2\, C_t^{i,2} \ldots + \phi_k\, C_t^{i,v} + \xi_{1,t} \qquad (5)$$

with ξ_1 the residual of this regression, i.e. the residual after the correlation between the indicator variables $1 \ldots v$ (or first principal components of groups $1 \ldots p$) is removed. The unique contribution $Corr^u$ can then be estimated by regressing the cycle of the reference series (C_t^r) on residual ξ_1,

$$C_t^r = c + \beta_1 \xi_{1,t} + \varepsilon_t \qquad (6)$$

This procedure is repeated for all indicator variables $1 \ldots v$ (and principal components $1 \ldots p$ of each group) as dependent variable in equation 5. The parameter β_1 represents $Corr^u$. The rebalanced weights w_i for indicator variables $1 \ldots v$ are then computed as,

$$w_i = \max_{6 \le n \le 18} \left| Corr\left(C_t^r, C_{t-n}^i\right)\right| + Corr^u \qquad (7)$$

with $\sum_{i=1}^{v} w_i = 1$ after rescaling. Equation 7 rebalances the weights by giving more weight to uncorrelated indicators. The unique contribution $Corr^u$ can be negative, implying that the indicator variable (or principal component of a group) negatively correlates with the reference series after controlling for the cross-correlation with the other indicator variables. A negative value of $Corr^u$ can lead to a negative weight w_i according to equation 7. This is undesirable if the leading variable is pro-cyclically related to the reference series (i.e. $\max_{6\leq n\leq 18} Corr\left(C_t^r, C_{t-n}^i\right) > 0$), implying that a negative correlation does not make sense. Weight w_i is then capped at 0.

Countercyclical variables are negatively correlated with the core inflation cycle (i.e. $\max_{6\leq n\leq 18} Corr\left(C_t^r, C_{t-n}^i\right) < 0$). In that case we multiply $Corr^u$ by -1 and include the variable with an inverted sign in the CLI. The countercyclical character of an indicator variable (or principal component) may be related to financial or economic channels. Examples of the former are the countercyclical pass-through of changes in the short-term interest rate and the exchange rate to aggregate demand. An economic channel for instance relates to supply bottlenecks, that may reflect economic disruption and uncertainty and so affect the economic outlook and core inflation.

The outcomes of the rebalanced weights are presented in the last column of Tables 6 (for the indicator variables) and Table 7 (for the principal components). Regarding the indicator variables in Table 6, the import price gets the largest weight in the CLI of NL, while global (OECD) inflation gets the largest weight in the CLI of the EA. The value added of the rebalanced weighting scheme is illustrated by the cap on the weight of variable selling price expectations of intermediate goods in the case of NL. This variable is highly correlated with selling price expectations of consumer goods, which requires an adjustment of the weight to avoid statistical double counting. Regarding the principal component approach in Table 7, the weights of NL and EA are quite similar. In both CLIs, external conditions get most weight and commodity prices least.

Table 6. Weights for indicator variables

A. NL

	Lead time	***Correl (C^r, C^i)***	***Correl^u***	***w_i***
Import prices	12	0.77	0.74	0.32
Selling price exp cons goods	13	0.82	0.19	0.22
Consumer expenditures	12	0.72	0.02	0.16
Producer confidence	18	0.55	0.06	0.13
Commodity prices non-energy	17	0.51	-0.13	0.08
PPI final goods prices	11	0.77	-0.52	0.05
House price	16	0.53	-0.33	0.04
Selling price exp interm goods	16	0.59	-0.65	0.00

B. EA

	Lead time	Correl (C^r,C^i)	Correl^u	w_i
OECD CPI	7	0.75	1.66	0.65
House price	12	0.79	0.02	0.22
Commodity prices non-energy	16	0.53	-0.06	0.13
CPI energy	11	0.50	-1.15	0.00

Rebalanced weights (w_i in last column) of indicator variable approach (based on 3m-3m changes). Lead time of the variable on the turning point in the reference series in months in first column. $Correl(C_t^r, C_{t-n}^i)$ is the correlation between the reference series and the variable. $Corr^u$ is the unique contribution of each variable to the indicator.

Table 7. Weights for the principal components

A. NL

	Lead time	Correl (C^r,C^i)	Correl^u	w_i
External conditions	10	0.74	0.73	0.40
Business cycle	18	0.54	0.20	0.20
Prices and costs	16	0.69	0.03	0.19
Price expectations	14	0.71	-0.39	0.09
Financial	13	0.38	-0.11	0.07
Commodity prices	14	0.65	-0.44	0.05

B. EA

	Lead time	Correl (C^r,C^i)	Correl^u	w_i
External conditions	9	0.75	1.13	0.44
Business cycle	17	0.66	0.35	0.24
Price expectations	13	0.74	-0.11	0.15
Prices and costs	13	0.79	-0.31	0.11
Financial	15	0.52	-0.22	0.07
Commodity prices	13	0.56	-0.58	0.00

Rebalanced weights (w_i in last column) of principal component approach (based on 3m-3m changes). Lead time of the principal component on the turning point in the reference series in months in first column. $Correl(C_t^r, C_{t-n}^i)$ is the correlation between the reference series and the principal components. $Corr^u$ is the unique contribution of each principal component to the indicator.

The CLI is constructed by weighting the indicator variables (and principal components in the second approach) with lag n, being the lag at which the correlation with the reference peaks (i.e. the lead time in Tables 6-7).

$$CLI = \sum_{i=1}^{v} w_i \, C_{t-n}^i \tag{8}$$

The lags reflect the lags in the transmission of inflation pressures embedded in the indicator variables to core inflation. The inclusion of the lags of indicator variables is in line with the forward looking character of the CLI. The length of the projection horizon is determined by the indicator variable (or principal component) with the shortest lead time. For NL this is 11 months in the indicator variable approach and

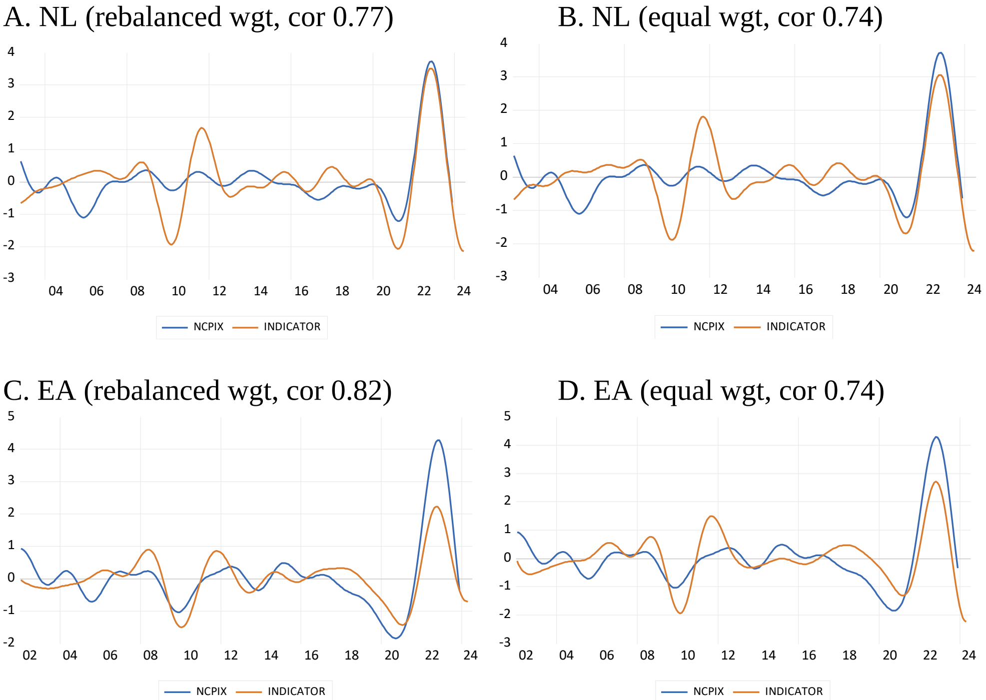
10 months in the principal component approach and for the EA this is 7 respectively 9 months.

6.2 Outcomes

Figure 8 shows the CLIs based on the indicator variable approach. As shown in Table 6, the NL CLI includes 8 variables and the EA CLI includes 4 variables that meet the turning point and correlation criterium. The correlation analysis shows that all these variables are pro-cyclical vis-à-vis the CPIX cycle. This also holds for the 6 principal components which make up the CLI. The CLI based on rebalanced weights tracks the core inflation cycle closer for the EA than for NL (Figure 8). Particularly in the aftermath of the global financial crisis (2008-2010) the CLI for NL does not fall like the CPIX cycle, while the CLI for the EA does.

The effects of the pandemic and the Ukraine war on the core inflation cycle are tracked more closely by the CLI for NL than by the CLI for the EA. In those periods, the troughs in de CPIX cycle and the CLI are synchronised in NL, while the Dutch CLI almost perfectly tracks the cyclical inflation peak in 2022. The CLI for the EA performs a bit less well in those years. Since Autumn 2023, the CPIX cycle has fallen below trend (i.c. below the horizontal axis). The CLIs predict that the cycle will remain below trend well into 2024. At the very end of the sample, the CLI for the EA suggests that a turning point in the CPIX cycle is in the offing.

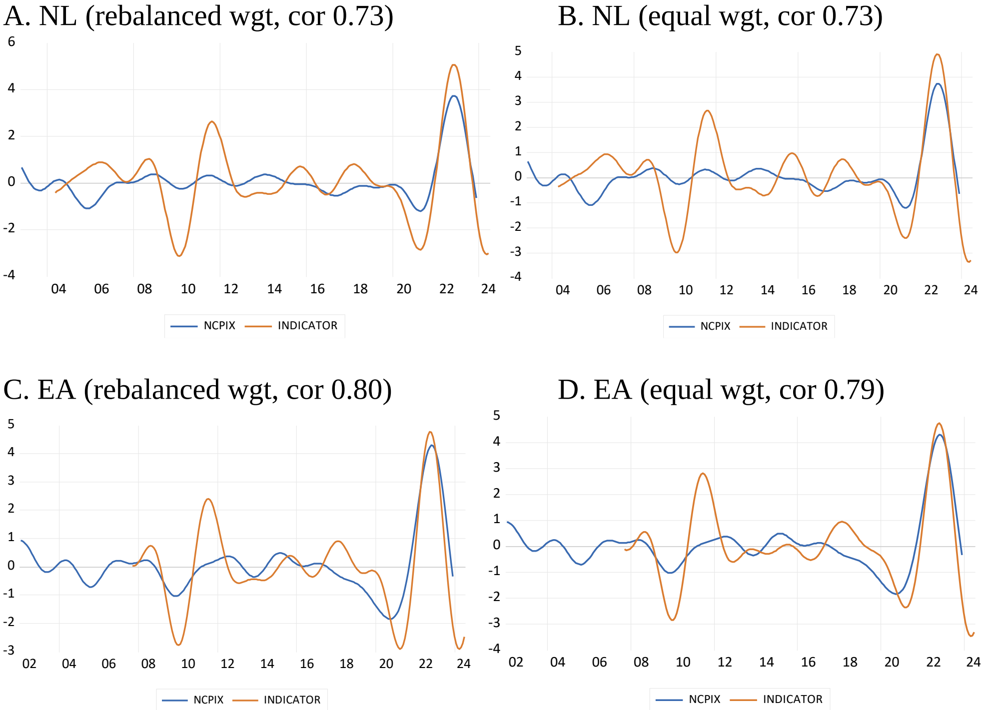
Figure 8. Composite indicator CLI and reference series CPIX (based on indicator variable approach)



Core inflation cycle (NCPIX) and CLI (indicator), based on 3m-3m changes in core inflation (CPIX). Indicator based on indicator variables and rebalanced (left-hand panels) and equal weights (right-hand panels).

Both in NL and the EA, the correlation between the CLI and the reference cycle is higher with rebalanced weights than with equal weights (rebalanced weights NL: 0.77, EA: 0.82 and equal weights NL: 0.74, EA: 0.74). The correlation of the CLI based on weights determined by principal component weighting approach is also lower than for the rebalanced weights (NL: 0.73, EA: 0.74). This underscores the value added of the rebalancing procedure. Compared to the indicator variable approach, the correlations are somewhat lower for the CLIs based on principal components of the variable groups, although the inflation surge in 2022 is well tracked by that approach as well (Figure 9).

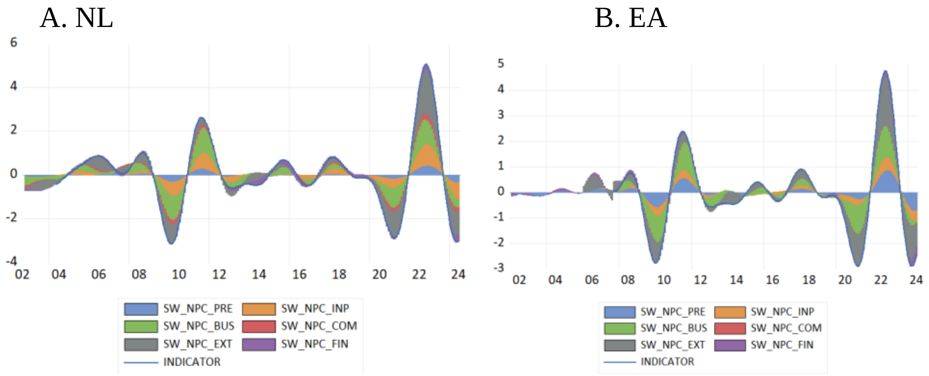
Figure 9. Composite indicator CLI and reference series CPIX (based on principal component approach)



Core inflation cycle and indicator, based on 3m-3m changes in core inflation (CPIX). Indicator based on the principal components approach and rebalanced (left-hand panels) and equal weights (right-hand panels).

The CLI can be decomposed by the contribution of the first principal component of each group as in Figure 10. Such decomposition displays the relative change across time of the contribution of each driver of the core inflation cycle. It shows that the business cycle component was most dominant in the aftermath of the global financial crisis (2008-2012), while the external conditions component was a relatively important driver during the Covid-19 pandemic and the Ukraine war. It suggests that the effects of these recent shocks on core inflation were to a relative large extent related to global conditions.

Figure 10. Decomposition of indicator for core inflation cycle



Decomposition of core inflation cycle indicator constructed by the principal component approach. SW_NPC_PRE is contribution of price expectations, SW_NPC_BUS is contribution of business cycle, SW_NPC_EXT is contribution of external conditions, SW_NPC_INP is contribution of prices and costs, SW_NPC_COM is contribution of commodity prices, SW_NPC_FIN is contribution of financial variables.

7. Probability of turning points

To estimate the probability of a turning point in the reference series we estimate two types of probit models: a binary probit model and an ordered probit model.

Formally, the binary probit model estimates the probability p that a binary response variable y = [0, 1] has value y = 1 given the outcomes of a set of independent variables x:

$$p = pr[y = 1|x] = F(x'\beta) \quad (9)$$

With y the dummy for a turning point in the reference series, which is 1 on the date of a turning point and 0 otherwise. p is the predicted probability of a turning point and $F(..)$ the cumulative standard normal distribution function.

In the ordered probit model, we distinguish the probability of a turning point at a peak from the probability of a turning point at a trough of the inflation cycle. Formally it means that variable y can take j alternative values,

$$y = j \text{ if } a_{j-1} < y \leq a_j$$

With probability p_j that variable y takes alternative value j,

$$\begin{aligned} p_j &= pr[y = j \mid x] = p\left(a_{j-1} < y \leq a_j\right) \\ &= F\left(a_j - x'\beta\right) - F\left(a_{j-1} - x'\beta\right) \end{aligned} \quad (10)$$

With y being the dummy variable indicating a turning point in the reference series, with y being equal to 2 for a turning point at a top in the cycle, 0 for a turning point at the trough and 1 otherwise.

For both the binary and ordered probit models, the set of independent variables x is comprised by the indicator variables selected in section 5. In particular, we include the interaction of the dummy for the turning points in the indicator variables ($D^{TP} = 1$ at the date of a turning point and 0 otherwise) with the first principal component of the cycles of the indicator variables $PC(C^i)$,

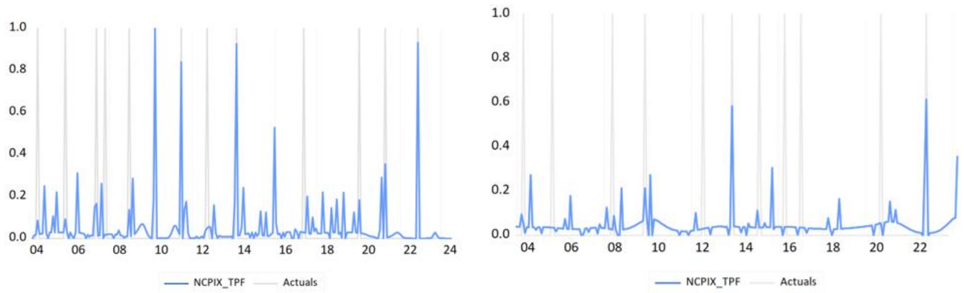
$$x' = \left(D^{TP}_{t-n},\ PC(C^i_{t-n}),\ D^{TP}_{t-n}\ PC(C^i_{t-n})\right) \tag{11}$$

We include several lags (n) of the dummies and indicator variables to take into account the leading property of the indicator variables for turning points in the reference series. After applying a general-to-specific estimation procedure for equations 10 and 11 we only keep the significant explanatory variables in the model. The principal component of the indicator variables ensures that we include continuous variables in the model, combined with the dummy variable for the turning points in the indicator variables.

The outcomes show that the binary probit model, estimated for probability *p* of the turning points in the core inflation cycle (*y*), has a higher fit for NL than for the EA (Figure 11). Occasionally the estimated probability spikes, also in 2022 during the aftermath of the pandemic.

Figure 11. Estimated probability of turning points (binary probit model)

A. NL (R2 0.37) B. EA (R2 0.13)

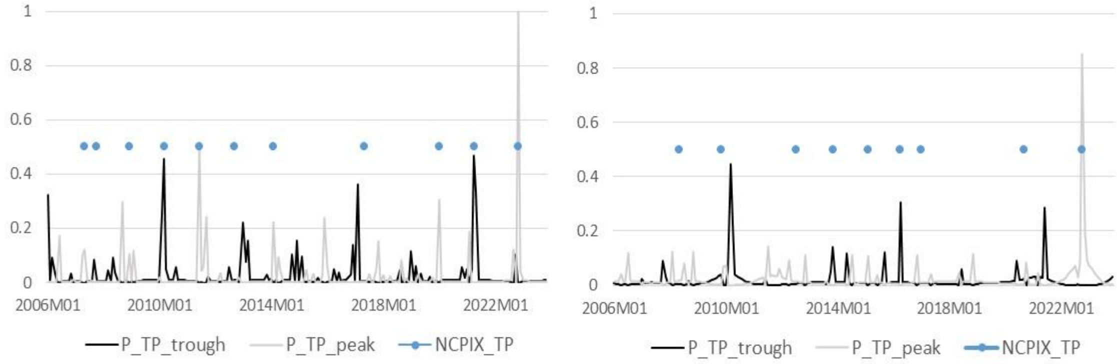


Probability of turning point estimated by binary probit model specified in equation 9. NCPIX_TPF is estimated probability of turning point in the cycle of core inflation. Actuals is the actual turning point in the cycle of core inflation.

The ordered probit shows that the estimated probability of a turning point reached the highest level at the peak of the inflation cycle in 2022, both for NL and the EA (Figure 12). Like in case of the binary probit, the outcomes of the ordered probit show that the model fit is higher for NL than for the EA. For NL the turning points at either the trough or the peak of the cycle are quite well reflected in the spikes of the estimated probabilities.

Figure 12. Estimated probability of turning points (ordered probit model)

A. NL (R2 0.38) B. EA (R2 0.22)



Probability of turning point estimated by ordered probit model specified in equation 10. P_TP_trough (P_TP_peak) is probability of turning point in the cycle of core inflation at a trough (peak) and NCPIX_TP is the date of the turning point in the cycle of core inflation.

8. Relation to forecast error

Although CLIs are not used to forecast macro-economic variables like inflation, they can complement forecasting models, such as structural macro-econometric models. Forecasts tend to be less accurate at cyclical turning points (An et al., 2018). Hence, the ability of our CLI to predict turning points can particularly add value at inflection points of inflation cycle.

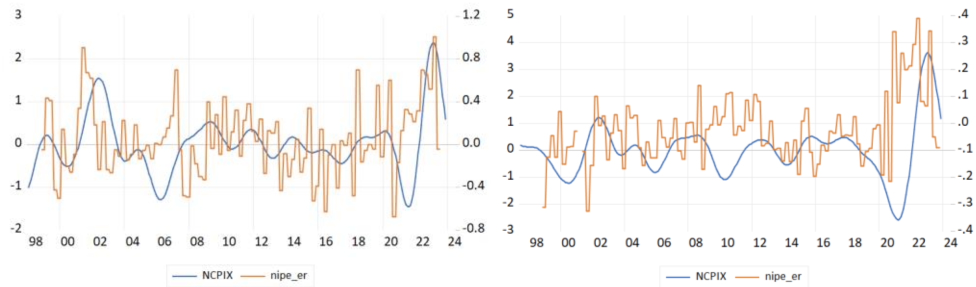
We test the hypothesis that inflation forecasts are less accurate at turning points in the core inflation cycle. For this we use the forecast errors of the narrow inflation projection exercise (NIPE) of the Eurosystem (ECB, 2016). For the NIPE, national central banks produce short-term forecasts for inflation, including core inflation, for their respective countries. The forecasts are made every quarter, over a horizon of 11 months, based on monthly data. The ECB aggregates the individual country inflation figures to obtain the euro area inflation path. The ECB (2016) mentions that forecast errors may arise due to unforeseen economic events, incomplete information, changes in the external assumptions and the impact of structural economic reforms. The NIPE forecast errors are based on the forecast of the y-o-y change of core inflation. The series capture the error in the first three months of the 11 months ahead forecast. We take the average error of these first three months.

Figure 13 suggests there is a relation between the NIPE forecast errors and the turning points in the core inflation cycle (the latter also based on y-o-y changes of core inflation). Eyeballing suggests that outliers in the forecast error seem to coincide with turning points in the core inflation cycle in 2002 (EA), 2008 (EA and NL), 2010 (EA), 2021 (EA) and 2023 (EA and NL).[6]

[6] The correlation between the series is higher for NL (+0.22) than for the EA (+0.09).

Figure 13. Forecast error and core inflation cycle

A. NL (cor 0.26) B. EA (cor 0.09)



Forecast error (nipe_er, right-hand axis) of forecasted y-o-y change of core inflation (average error of the first three months of the forecast horizon). Core inflation cycle (NCPIX, left-hand axis) based on y-o-y changes of core inflation.

To test whether turning points in the core inflation cycle explain the forecasts errors (ε^f), we estimate the following equation,

$$\varepsilon_t^f = \alpha + \beta_1 y_t + \beta_2 CLI_t + \beta_3 \, y_t \, CLI_t + \varepsilon_t \qquad (12)$$

With y the dummy variable for a turning point in the core inflation cycle, which is 1 on the date of a turning point at the peak, -1 for a turning point at the trough and 0 otherwise. CLI is the composite indicator, based on the indicator variable approach, y-o-y changes and rebalanced weights. The coefficient of interest is β_3, which indicates to what extent the interaction of the dummy and the indicator explains forecast error ε^f. In case $\beta_3 > 0$ a turning point in the core inflation cycle is associated with a higher error in the inflation forecast.[7] The regression results in Table 8 show that this coefficient is significantly positive for both NL and the EA. This suggests that the hypothesis that inflation forecasts are less accurate at turning points in the core inflation cycle cannot be rejected. For NL, the R2 indicates that 12% in the variance of the forecast error can be explained by the model. The R2 drops to 1% if the equation is estimated on pre-Covid data. This suggest that forecast errors during Covid drive the results.

Table 8. Regression results, full sample

	Dependent variable: NIPE forecast error ε_t^f	
	NL	**EA**
Constant (α)	0.03 (0.03)	-0.01 (0.01)
Indicator (CLI)	0.09** (0.04)	0.01 (0.02)
Dummy turning point (y)	0.05 (0.07)	-0.00 (0.02)
Interaction (y CLI)	0.18*** (0.06)	0.02** (0.01)
Obs.	225	253
R2	0.12	0.01

*Estimation outcomes of equation 12. HAC standard errors between brackets. ***, **, * statistical significance at 1, 5, 10% level. Sample NL: 2004m11-2023m7, sample EA: 2002m10-2023m10.*

[7] Both on the case of a turning point at the peak and at the trough the interaction term is positive, since at the peak (trough) both y and CLI are positive (negative).

Furthermore, we test whether a turning point at the peak or the trough of the inflation cycle makes a difference for the forecast error. For this we extend equation 12 with a dummy for the regime of the cycle, with dummy $r_t^{CLI} = 1$ if the cycle is above trend (peak) and 0 otherwise (vice versa if the cycle is below the trend, or at a trough),

$$\varepsilon_t^f = \alpha + \beta_1 y_t + \beta_2 CLI_t + \beta_3 r_t^{CLI} + \beta_4 \, y_t \, CLI_t \, r_t^{CLI} + \varepsilon_t \tag{13}$$

The regression results in Table 9 show that this coefficient of the interaction term including the regime dummy is significantly positive for NL in both regimes. The coefficient is higher when the cycle is below trend, i.c. at a trough. For the EA the coefficient of the interaction term is only significant in the below trend regime (i.c. at a trough). This suggests that the hypothesis that inflation forecasts are less accurate at turning points in the core inflation cycle most likely holds for turning points at the trough of the inflation cycle.

Table 9. Regression results, by regime

	Dependent variable: NIPE forecast error ε_t^f			
	NL		**EA**	
	peak	trough	peak	trough
Constant (α)	0.10 (0.06)	-0.03 (0.05)	-0.01 (0.03)	-0.02 (0.02)
Indicator (CLI)	0.13*** (0.04)	0.14*** (0.05)	0.01 (0.03)	0.01 (0.03)
Dummy turning pnt (y)	-0.02 (0.07)	0.15 (0.09)	-0.01 (0.02)	0.01 (0.03)
Dummy regime (r^{CLI})	-0.13 (0.09)	0.13 (0.09)	-0.01 (0.03)	0.03 (0.03)
Interaction ($y \, CLI \, r^{CLI}$)	0.19*** (0.07)	0.35*** (0.13)	0.01 (0.03)	0.04* (0.02)
Obs.	250	250	253	253
R2	0.13	0.13	0.01	0.01

*Estimation outcomes of equation 13. HAC standard errors between brackets. ***, **, * statistical significance at 1, 5, 10% level. Sample NL: 2004m11-2023m7, sample EA: 2002m10-2023m10.*

9. Robustness tests

As robustness test, we construct the CLI for the sub-sample up to the pandemic (2019m12). Figures 8 and 9 show that the CLI has a high fit with the reference series during the most recent years, which suggests that extreme movements in core inflation – driven by the inflation shocks of the pandemic and the Ukraine war, dominate the composition of the CLI.

When we apply the individual variable approach on the sub-sample, different variables meet the selection criteria (described in Section 5) compared to the selection based on the full sample. For the EA, this concerns three out of the four variables (only house prices are selected in both samples). For NL, no indicator variable meets the criteria in the sub-sample. Therefore we only construct the CLI based on the principal component approach. That includes all variables with different loadings (the implicit weights) in each sample period. This makes the principal component approach by construction more robust to changes in the sample period.

The outcomes in Annex 2 for the sub-sample up to 2019m12 show that the CLI performs relatively well for the EA. The correlation is somewhat lower compared to the full sample, while the turning points of the CLI match the turning points of the reference series quite well. This holds both for the individual variable approach, as well as for the principal component approach. For NL, the outcome based on the sub-sample period show that the CLI (based on principal components) performs much worse compared to the CLI based on the full sample. In the sub-sample, the CLI fluctuates much more than the reference series and the correlation between both is low. From this we conclude that the CLI for NL is not robust to the exclusion of the pandemic period, while the CLI for the EA is to a larger extent robust.

10. Conclusion

The non-parametric indicator (CLI) that we developed has leading properties for turning points in the core inflation cycle. We add to the related literature by combining turning point matching and dynamic correlation for the selection of the variables in the CLI, while the weights are adjusted for cross-correlation between the variables. Another contribution is that we construct the CLI based on individual indicator variables and a principal component approach.

The principal component approach applied to core inflation in NL and the EA shows that the business cycle component was most dominant in the aftermath of the global financial crisis (2008-2012), while the external conditions component was a relatively important driver of the core inflation cycle during the Covid-19 pandemic and the Ukraine war. It suggests that the effects of these shocks on core inflation were to a relative large extent related to global conditions. The CLI based on the individual indicator variables and the principal components approach indicate that the core inflation cycle in NL and the EA will remain below trend well into 2024.

By predicting turning points in the core inflation cycle, the CLI complements macroeconomic or time series models that are used to forecast inflation. Moreover, structural forecasting models tend to be less accurate at cyclical turning points and so the information produced by the CLI particularly adds value at inflection points of the inflation cycle. We show that turning points in the core inflation cycle explain forecast errors of core inflation in NL and the EA. Further research is needed to develop an analytical framework for monetary policy analyses that combines turning point indicators with structural forecasting models.

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Annex 1. Variables

Groups	*Indicator variables*	*start sample*	*frequency*	*log*	*source*
Reference series	Core inflation (CPIX)	EA: 96m1; NL: 60m4	EA: m; NL: m	no	EA & NL: OECD
Business cycle	Consumer expenditures	EA: 85q2; NL: 77m2	EA: q; NL: m	yes	EA: ECB; NL: CBS
	Industrial production	EA: 91m1; NL: 79m12	EA: m; NL: m	yes	EA: ECB; NL: CBS
	Producer confidence	EA: 85m1; NL: 85m1	EA: m; NL: m	no	EA: EC; NL: CBS
	Consumer confidence	EA: 85m1; NL: 86m4	EA: m; NL: m	no	EA: EC; NL: CBS
	PMI manufacturing	EA: 98m7; NL: 00m3	EA: m; NL: m	no	EA & NL: ISM
	IFO index	EA: 91m1; NL: 91m1	EA: m; NL: m	no	EA & NL: IFO
	Industry capacity utilization	EA: 85q2; NL: 89q1	EA: q; NL: q	yes	EA: ECB; NL: CBS
	Vacancy indicator	EA: 86q1; NL: 99m1	EA: q; NL: m	no	EA: EC; NL: CBS
Prices and costs	PPI final goods prices	EA: 95m1; NL: 00m1	EA: m; NL: m	no	EA: ECB; NL: CBS
	PPI intermediate goods prices	EA: 95m1; NL: 00m1	EA: m; NL: m	no	EA & NL: Eurostat
	PMI sales prices	EA: 97m6; NL: 02m10	EA: m; NL: m	no	EA & NL: ISM
	PMI purchase prices	EA: 02m10; NL: 00m3	EA: m; NL: m	no	EA & NL: ISM
	Wages	EA: 95q3; NL: 91m1	EA: q; NL: m	no	EA: ECB; NL: CBS
Price expectations	Selling price expectations intermediate goods	EA: 85m1; NL: 90m11	EA: m; NL: m	no	EA: EC; NL: EC
	Selling price expextations consumer goods	EA: 85m1; NL: 90m11	EA: m; NL: m	no	EA: EC; NL: EC
	Inflation expectation (Refinitive)	EA: 85m1; NL: 96m1	EA: m; NL: m	no	EA & NL: Refinitive
	Inflation expectations (Consensus Economics)	EA: 89m11; NL: 89m11	EA: m; NL: m	no	EA & NL: Consensus

Groups	*Indicator variables*	*start sample*	*frequency*	*log*	*source*
Commodity prices	Commodity price index non-energy	EA: 80m1; NL: 80m1	EA: m; NL: m	yes	EA & NL: ECB
	Commodity price index energy	EA: 80m1; NL: 80m1	EA: m; NL: m	yes	EA & NL: ECB
	Oil price (Brent Europe)	EA: 87m7; NL: 87m7	EA: m; NL: m	yes	EA & NL: Fred
	CPI energy	EA: 96m1; NL: 60m4	EA: m; NL: m	no	EA & NL: OECD
External conditions	Global supply chain index	EA: 98m1; NL: 98m1	EA: m; NL: m	yes	EA & NL: Fed NY
	OECD CPI	EA: 70m1; NL: 70m1	EA: m; NL: m	yes	EA & NL: OECD
	Import prices	EA: 05m1; NL: 90m1	EA: m; NL: m	no	EA: Eurostat; NL: CBS
	Euro dollar	EA: 85m1; NL: 85m1	EA: m; NL: m	no	EA & NL: ECB
Financial	House price	EA: 92q1; NL: 70m1	EA: q; NL: m	yes	EA: ECB; NL: CBS
	Long-term nominal interest rate	EA: 70m1; NL: 70m1	EA: m; NL: m	no	EA & NL: Fred
	Short-term real interest rate	EA: 70m1; NL: 70m1	EA: m; NL: m	no	EA & NL: Fred
	Yield spread	EA: 70m1; NL: 70m1	EA: m; NL: m	no	EA & NL: Fred
	Corporate credit spread	EA: 70m1; NL: 70m1	EA: m; NL: m	no	EA & NL: Fred
	Stock index	EA: 70m1; NL: 87m1	EA: m; NL: m	yes	EA: ECB; NL: CBS
	Gold price	EA: 68m2; NL: 68m2	EA: m; NL: m	yes	EA & NL: Bullionvault
	M3	EA: 80m1; NL: 80m1	EA: m; NL: m	yes	EA & NL: ECB
	M1	EA: 80m1; NL: 80m1	EA: m; NL: m	yes	EA & NL: ECB

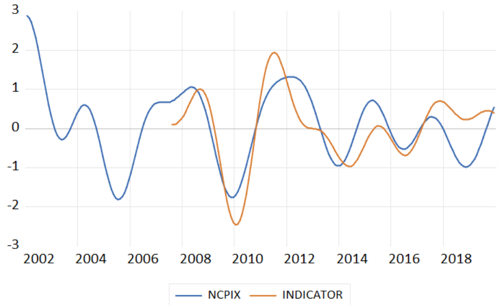
Note: CPIX for NL is adjusted for VAT (value added tax) changes. CPI is consumer price index. Long-term nominal interest rate is 10 years government bond yield. Short-term real interest rate is 3 months money market rate minus 1 year ahead expected inflation (Consensus Economics). Yield spread is long-term nominal interest rate minus 3 month money market rate. Corporate bond spread is Moodys BAA corporate bond yield minus 10 years US government bond yield. M1, M3 are monetary aggregates.

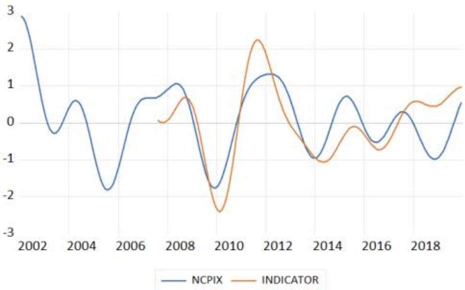
Annex 2. Robustness tests, sample period 2001m1 – 2019m12

Individual variable approach

A. EA (rebalanced wgt, cor 0.75)

B. EA (equal wgt, cor 0.72)



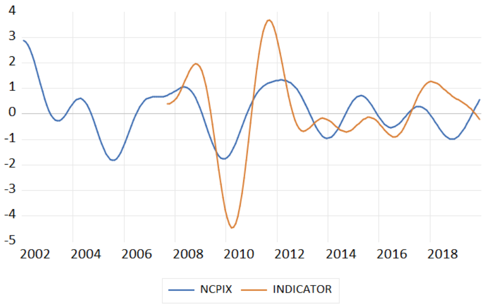


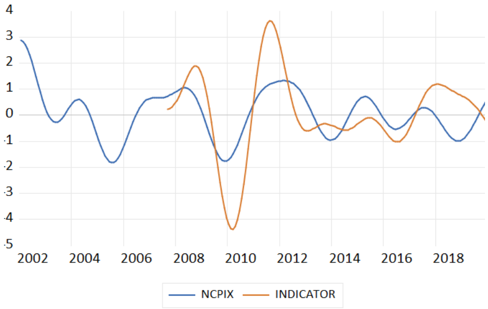
Core inflation cycle and indicator, based on 3m-3m changes in core inflation (CPIX) and sample period 2001m1 – 2019m12. Indicator based on the indicator variable approach and rebalanced (left panels) and equal weights (right panels).

Principal component approach

A. EA (rebalanced wgt, cor 0.64)

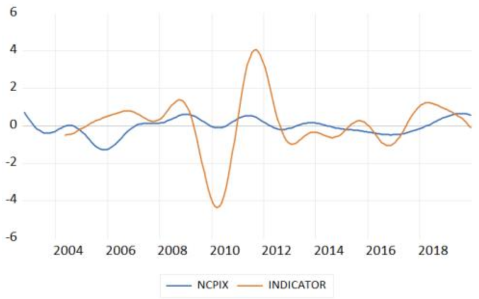
B. EA (equal wgt, cor 0.67)

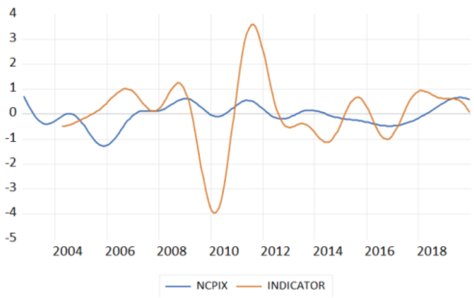




C. NL (rebalanced wgt, cor 0.20)

D. NL (equal wgt, cor 0.19)





Core inflation cycle and indicator, based on 3m-3m changes in core inflation (CPIX) and sample period 2001m1 – 2019m12. Indicator based on the principal components approach and rebalanced (left panels) and equal weights (right panels).

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De Nederlandsche Bank N.V.
Postbus 98, 1000 AB Amsterdam
020 524 91 11
dnb.nl