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Underlying inflation measures for Germany

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Non-technical summary

Research Question

Maintaining price stability is key for central banks. Within a medium-term monetary policy framework, many central banks pay close attention to underlying inflation measures, which should reflect broad-based price developments and abstract from short-term volatility or idiosyncratic movements. Traditional measures of underlying inflation are based on the ex ante exclusion of certain volatile price items, such as core inflation or trimmed means. Nevertheless, these measures can suffer from temporary price shocks and might miss early signals of underlying inflation. We assess how alternative, data-driven measures improve the assessment of underlying inflation in Germany compared to traditional exclusion-based approaches.

Contribution

In this technical note, we construct and present the in-sample and out-of-sample properties of various underlying inflation measures for Germany. In doing so, we enrich the traditional exclusion-based set of indicators with more sophisticated methods from econometric models, machine learning, and micro price evidence. This allows us to capture different concepts and improve the robustness of the range of underlying inflation measures, ensuring that they better capture the medium-term inflation trend in Germany. In particular, we present the analysis in greater detail here, the main results of which were published in the Monthly Report of May 2025.

Results

Compared to traditional exclusion-based measures, we find that the set of alternative underlying inflation measures has generally a lower volatility, a lower bias and a higher out-of-sample forecasting accuracy. However, we find no evidence that any single measure clearly outperforms the others over time. Nevertheless, the range of alternative indicators identified the turning points towards higher inflation and the subsequent disinflation process somewhat earlier than the traditional ones. For policy makers, this implies that a range of model-based measures should be taken into account when monitoring underlying inflation. Finally, we show that according to all measures, underlying inflation is highly sensitive to monetary policy shocks and declines in response to a contractionary shock, with the bulk of reaction taking place between one to three years after the shock.

Nichttechnische Zusammenfassung

Fragestellung

Die Wahrung der Preisstabilität ist zentral für Notenbanken. Im Rahmen einer mittelfristig ausgerichteten Geldpolitik legen viele Zentralbanken besonderes Augenmerk auf Maße der zugrunde liegenden Inflation, die breit angelegte Preisentwicklungen widerspiegeln und kurzfristige Volatilität oder idiosynkratische Schwankungen ausblenden sollen. Traditionelle Maße basieren auf dem ex ante-Ausschluss bestimmter volatiler Preispositionen, wie beispielsweise Kerninflation oder getrimmte Mittelwerte. Diese Ansätze können jedoch durch vorübergehende Preisschocks beeinflusst werden und frühe Signale der zugrunde liegenden Inflation übersehen. In der vorliegenden Analyse untersuchen wir, inwieweit alternative, datenbasierte Ansätze die Beurteilung der zugrunde liegenden Inflation in Deutschland gegenüber traditionellen Maßen verbessern.

Beitrag

In dieser *Technical Note* werden die In-sample- und Out-of-sample-Eigenschaften verschiedener Maße der zugrunde liegenden Inflation für Deutschland dargestellt. Dabei werden traditionelle, ausschlussbasierte Indikatoren um Ansätze aus ökonometrischen Modellen, dem maschinellen Lernen und anhand von Mikropreisevidenz erweitert. Dies ermöglicht es, unterschiedliche Konzepte der zugrunde liegenden Inflation abzubilden und die Robustheit der Spannbreite an Indikatoren zu erhöhen, um den mittelfristigen Inflationstrend in Deutschland präziser zu erfassen. Die Analyse wird hier in erweiterter Form präsentiert; die Hauptergebnisse wurden im Monatsbericht vom Mai 2025 veröffentlicht.

Ergebnisse

Im Vergleich zu traditionellen Maßen weist die Gruppe alternativer Indikatoren für die zugrunde liegende Inflation insgesamt eine geringere Volatilität, eine niedrigere Verzerrung und eine höhere Out-of-sample-Prognosegenauigkeit auf. Allerdings gibt es kein Maß, das den anderen konsistent überlegen ist. Gleichwohl identifizieren die alternativen Indikatoren die Wendepunkte hin zu höheren Inflationsraten und den anschließenden Disinflationsprozess etwas früher als die traditionellen Maße. Für die Geldpolitik bedeutet dies, dass bei der Beurteilung der zugrunde liegenden Inflation eine Vielzahl modellbasierter Indikatoren berücksichtigt werden sollte. Schließlich zeigt die Analyse, dass alle betrachteten Maße eine hohe Sensitivität gegenüber geldpolitischen Schocks aufweisen und nach einem restriktiven Schock deutlich zurückgehen, wobei der größte Teil der Reaktion innerhalb von ein bis drei Jahren erfolgt.

Underlying inflation measures for Germany*

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Abstract

In this paper, we evaluate a set of measures of underlying inflation for Germany using conventional measures, such as core inflation (excluding energy and food items), and alternative measures based on econometric models, machine learning, and micro-price evidence. We compare these measures through detailed in-sample and out-of-sample evaluations. The alternative measures exhibit lower volatility, minimal bias, and superior out-of-sample forecasting accuracy performance. While we find no evidence that any single measure clearly outperforms the others over time, the range of alternatives measures also reflects a somewhat earlier uptick and downturn in light of the recent inflation surge in comparison to traditional ones. In addition, all measures under consideration are highly sensitive to monetary policy shocks.

Keywords: Underlying inflation, monetary policy, local projections, machine learning.

JEL codes: E31; E37; C22.

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1 Introduction

Maintaining price stability is key for central banks. Monitoring only headline inflation can be misleading due to high-frequency volatility, which might be irrelevant for a medium-term oriented monetary policy. To this end, policymakers often validate their inflation narrative by paying close attention to different measures of underlying inflation. However, the latter is unobserved, and can be understood in different terms.[1] In ECB monetary policy communications, underlying inflation is defined as capturing *"more persistent and generalised developments across prices, abstracting from volatile or idiosyncratic relative price movements"* and providing *"an informative signal about where headline inflation will settle in the medium term"* (Bańbura et al., 2023).

Traditional measures of underlying inflation are based on the ex ante exclusion of certain price items, either defined according to rigid backward-looking behaviour or by temporarily excluding items above a certain percentile of price changes. A prominent example is core inflation (excluding all energy and food items). Exclusion-based indicators can, however, still be affected by temporary shocks (Forni et al., 2005; Dolmas, 2005). For example, temporary tax cuts or other one-off effects are also reflected in core inflation measures but may not be relevant for underlying inflation. In addition, the exclusion of certain items may remove early signals of underlying inflation that are present in the tails of the price distributions.

For the euro area, the ECB monitors a wide set of underlying inflation indicators (Bańbura et al., 2023). These exclusion- and model-based measures all relate to the ECB's inflation target, the Harmonised Index of Consumer Prices (HICP), and have received increasing attention in monetary policy decisions since the recent surge in inflation. In this vein, Philip R. Lane, member of the Executive Board of the ECB, pointed out at the "Inflation: Drivers and Dynamics Conference 2024": *"The concept of underlying inflation plays a central role in the conduct of the ECB's monetary policy: our interest rate decisions are based on our assessment of the inflation outlook in light of the incoming economic and financial data, the dynamics of underlying inflation and the strength of monetary policy transmission."*[2]

[1] See Ehrmann et al. (2018) for a comparison of underlying inflation measures across major central banks. For example, Rudd (2020) emphasises the longer-term nature of underlying inflation (*"...the rate of inflation that would be expected to eventually prevail in the absence of economic slack, supply shocks, idiosyncratic relative price changes, or other disturbances."*), while Sbordone and Almuzara (2024) refer to "core" inflation, which *"reflects the need of downweighing volatile and likely transitory factors that especially when large, make difficult the assessment of inflationary pressures."*

[2] Underlying inflation is also often cited in the ECB Governing Council's monetary policy statements. See, for example, the ECB's monetary policy statement of 30 January 2025: *"The Governing Council today decided to lower the three key ECB interest rates by 25 basis points. In particular, the decision [...]*

In this technical note, we construct and present comprehensive in-sample and out-of-sample properties of several underlying inflation measures for Germany. In doing so, we enrich the traditional set of indicators with methods from conventional econometric models, machine learning and micro-price evidence. This allows us to capture different concepts and improve the robustness of the range of underlying inflation measures, ensuring that they better capture the medium-term inflation trend in Germany. In particular, we add the following measures to the standard set of (exclusion-based) underlying inflation measures for Germany:

(i) The *Persistent Common Component of Inflation (PCCI)*, following Bańbura and Bobeica (2020), assumes that the inflation rate of each individual item in the HICP basket can be decomposed into two orthogonal components: A common inflation component, driven by systemic shocks that affect all inflation series and capture most of the cross-sectional dimension, and an idiosyncratic component due to measurement error and sectoral shocks. The PCCI measure is obtained by aggregating the low frequency components using expenditure weights.

(ii) *Albacore* by Goulet Coulombe et al. (2024) is based on a machine learning algorithm trained to maximally predict future headline inflation. Specifically, the Albacore model adjusts the weights of HICP sub-indices to ensure that the adjusted measure is the most accurate predictor of future headline inflation.

(iii) The *Sticky-Price Indicator* proposed by Bryan and Meyer (2010) is derived from micro-price evidence on price setting. The authors argue that the sticky-price indicator is more forward-looking than its flexible counterpart and provides useful information for assessing where future inflation is heading. In our setup, an item is classified as sticky if it has a relatively low frequency of price changes, according to price-setting statistics for Germany documented in Gautier et al. (2024). These sticky price items are then aggregated into an indicator according to their relative share in the HICP basket.

(iv) Finally, *Supercore* has a direct link to macroeconomic developments; it is based on a reduced-form Phillips curve regression and includes only core items that are sensitive to the output gap. While it is less clear from a theoretical perspective whether Supercore captures the inflation trend, it is assumed to provide signals of underlying domestic inflationary pressures and is therefore regularly monitored by the ECB (Ehrmann et al., 2018).

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is based on its updated assessment of the inflation outlook, the dynamics of underlying inflation and the strength of monetary policy transmission."

In a next step, we evaluate the performance of these alternative measures in comparison with standard exclusion-based measures using both in-sample and out-of-sample evaluation metrics. Given the considerable impact of energy price shocks and the effects of the pandemic, we conduct our analyses on the full sample and a sub-sample ending in December 2019. Our comparison shows that the alternative measures for Germany exhibit lower volatility and bias and show significant improvements concerning out-of-sample forecasting performance over the traditional measures. Nevertheless, we find that there is no single measure outperforming the others over time. However, the range of alternative indicators identified the turning points towards higher inflation and the subsequent disinflation process somewhat earlier than the traditional ones.

In addition to in-sample and out-of-sample evaluation metrics, we further examine the sensitivity of the underlying inflation measures to euro area-wide monetary policy shocks as constructed by Jarociński and Karadi (2020). As expected, monetary policy shocks result in a decline in underlying inflation measures, with most of this decrease materialising within a 36-month period. These results remain both quantitatively and qualitatively similar when we impose a different lag structure and sample period for the empirical specification.

The structure of this technical note is as follows: In Section 2, we present the underlying inflation dataset and the theoretical background of the underlying inflation measures. In Section 3, we conduct a comprehensive in-sample and out-of-sample evaluation exercise to assess the performance of each measure. In Section 4, we assess the sensitivity of the underlying inflation measures to monetary policy shocks. Section 5 concludes the paper.

2 Underlying inflation measures

In this section we provide an overview of the disaggregated inflation data for Germany as well as of five different model classes of the underlying inflation measures at hand: (i) traditional exclusion-based measures such as core inflation, (ii) a common component measure derived from dynamic factor estimation (PCCI), (iii) a measure based on machine learning methods that selects maximally predictive items for headline inflation (Albacore), (iv) a sticky-price indicator derived from micro-price evidence and (v) a measure based on output-sensitive items (Supercore).

2.1 Database: Disaggregate price indices for Germany

Our analysis is based on more than 90 price index series underlying the official HICP in Germany. These series correspond to 4-digit level of the European Classification of Individual Consumption according to Purpose (ECOICOP), e.g. "01.1.1 Bread and cereals".[3] Our sample covers monthly data from January 2001 to December 2024.

In Table A1, we provide a list of all product items at the COICOP-4 level, together with their special aggregate category (e.g. non-energy industrial goods, NEIG) and their corresponding expenditure share.[4] While the COICOP-4 level consists of 94 items, due to data limitations, we exclude two items for Germany: (i) "03.1.1 Clothing materials" and (ii) "09.2.3 Maintenance and repair of other major durable goods for recreation and culture".[5] The exclusion of these series does not affect our results as their combined weight in the German HICP basket is always below 0.16%.

For most of the underlying inflation measures, we use year-on-year rates of change in the index series. When applying model-based methods to derive underlying inflation, it is typically necessary to use seasonally adjusted month-on-month rates of change. In our set of indicators, this is the case for PCCI, Albacore and Supercore. For this purpose, we seasonally adjust the COICOP-4 price indices using JDemetra+, an open source software widely recommended for the seasonal adjustment of official statistics in Europe.[6]

2.2 Traditional exclusion-based measures

One set of underlying inflation measures often used in monetary policy communication is exclusion-based measures. The idea here is to abstract from volatile items in the consumption basket *a priori*, i.e. such as energy and food items. Figure 1 depicts typical exclusion-based measures of underlying inflation for Germany. These include (i) headline inflation excluding energy (`HICPXE`), (ii) headline inflation excluding energy and food prices (`HICPXEF`), and (iii) headline inflation excluding food, energy, travel-related items and clothing (`HICPXEFTC`). The latter is often used to assess the underlying inflation trend for Germany, as package holidays in particular are a highly volatile and erratic

[3] Note that this classification is the same for all countries within the European Union. The lowest level of the HICP is ECOICOP-5, but these series only start in 2017. See Eurostat (2024) for more information on the HICP methodology.

[4] Eurostat's definition of special aggregates has changed in 2019 to the ECOICOP-5 level (see Eiglsperger, 2019). However, due to the late start of the ECOICOP-5 series only in 2017, we refer here to the broader classification based on COICOP-4 items.

[5] The price index for COICOP 03.1.1 contains missing values for the period 2008–2012, while the COICOP 09.2.3 series only starts in December 2014.

[6] See https://www.bundesbank.de/en/statistics/-/jdemetra--729580.

series (see Deutsche Bundesbank, 2017, and Schnorrenberger et al., 2024). Finally, (iv) trimmed means temporarily exclude large price changes that can also occur in typically non-volatile items. Based on the 92 year-on-year rates of change in the German HICP in a given month, the 10% (30%) trimmed mean removes 5% (15%) from the tails of the distribution of price changes. The remaining rates are aggregated to the trimmed measure using rescaled HICP weights. Similarly, the weighted median is the 50% weighted percentile of these price changes.

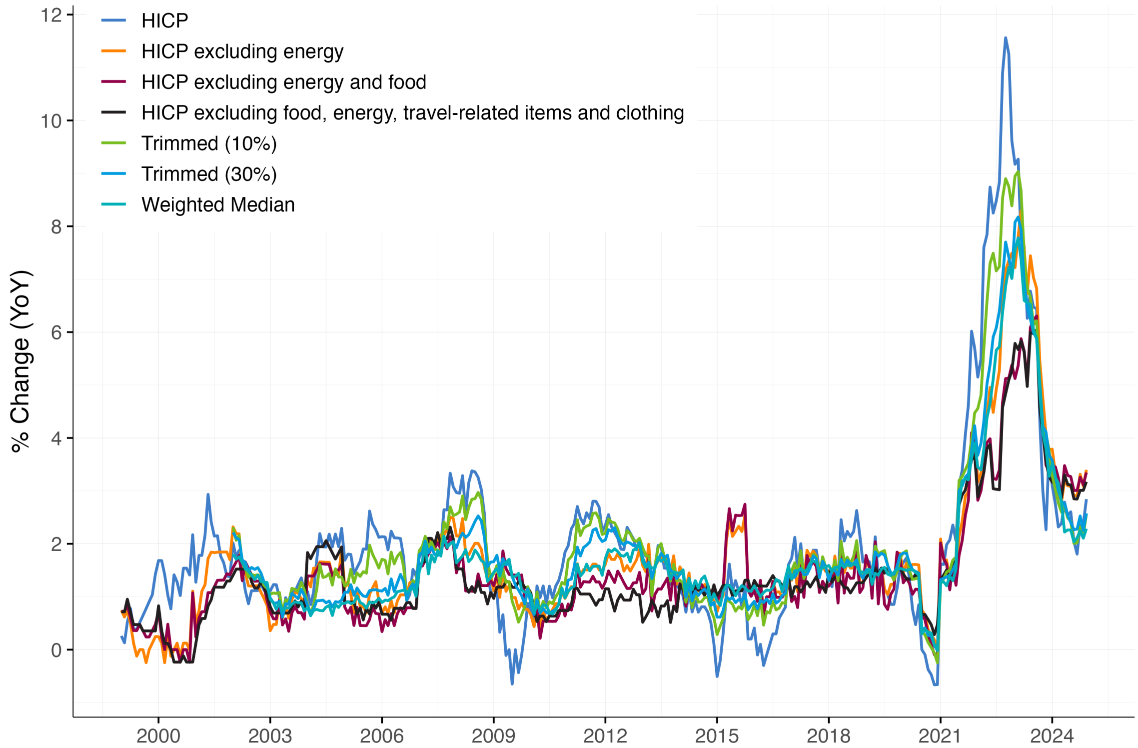


Figure 1: Headline and traditional exclusion-based measures of underlying inflation

As shown Figure 1, price dynamics in Germany during the first two decades of the euro were characterised by a relatively low rate of inflation. Over the period 2001-2019, the average annual rate of headline inflation was only 1.5%, while that of the HICP excluding energy and food was 1.2% and that of the HICP excluding energy, food, travel-related items and clothing was 1.1%. In the wake of the global Covid-19 pandemic in 2020 and Russia's invasion of Ukraine in 2022, there has been a notable increase in both the magnitude and volatility of the exclusion-based underlying inflation measures. Following the recent energy crisis, German headline inflation reached an all-time high of almost 12% (see Figure 1). In addition, headline inflation excluding energy and excluding energy and food exceeded 8% and 6%, respectively. Although excluding energy, food, travel, and clothing from headline inflation provides a somewhat smoother picture of underlying inflation in Germany, excluding price items *a priori* may come at the cost of losing valuable early signals. To overcome this shortcoming, we consider alternative underlying inflation measures in the following subsection.

2.3 Alternative measures of underlying inflation

2.3.1 Persistent Common Component of Inflation (PCCI)

The first alternative underlying inflation measure is the Persistent Common Component of Inflation (PCCI), as outlined in Bańbura and Bobeica (2020). The PCCI measure is based on the idea that the price dynamics of each individual item in the HICP basket can be decomposed into two orthogonal components. The first is a common component of inflation, driven by systemic shocks that affect all price items together and captures most of the cross-sectional dimension. The second one is an idiosyncratic component resulting from measurement error and sector-specific shocks. Accordingly, the rate of price change of each item is decomposed into two parts:[7]

$$x_{i,t} = \chi_{i,t} + \xi_{i,t} \tag{1}$$

where $x_{i,t}$ is the inflation rate (here: month-on-month rate of price change) of a given item i in the HICP basket, t is time, $\chi_{i,t}$ is the common and $\xi_{i,t}$ is the random component. The common component of inflation can be written as a linear combination of contemporaneous and lagged q dynamic factors as:

$$\chi_{i,t} = \sum_{k=1}^{q} \lambda_{i,k}(L) f_{k,t}, \tag{2}$$

where λ captures the effects of common factors. The common component can be further written as a sum of low and high frequency components in spectral domains. The low-frequency component is of interest as it removes temporary shocks and noise from each item in the HICP basket, thus providing a more accurate picture of the underlying inflation trend. In particular,

$$\chi_{i,t} = \chi_{i,t}^{L} + \chi_{i,t}^{H} \tag{3}$$

where $\chi_{i,t}^{L}$ and $\chi_{i,t}^{H}$ denote the low and high frequency components, respectively.[8] Following Bańbura and Bobeica (2020), we take three years as the threshold for the periodicity of

[7] We follow here the notation of Cristadoro et al. (2005) and Bańbura and Bobeica (2020).

[8] More details of the estimation of the low-frequency component can be found in Forni et al. (2005).

the low-frequency component and set $q = 16$.[9] The PCCI measure is then aggregated as:

$$PCCI_t = \sum_{i=1}^{N} w_{i,t} \times \chi_{i,t}^{L}, \tag{4}$$

where N is the total number of HICP items in the German dataset and $w_{i,t}$ is the respective expenditure weight of a given item. In our application, we consider two measures: $PCCI$ is based on all COICOP-4 items of the German HICP, while $PCCIcore$ is based on only 73 core items of the HICP.

Note that the resulting estimate of underlying inflation from PCCI may change with a new release of inflation data. We address this issue in a real-time analysis in Section 3.

2.3.2 Albacore

Our second underlying inflation measure is Albacore (Adaptive Learning-Based Core Inflation), recently introduced by Goulet Coulombe et al. (2024). The authors propose an assemblage regression – a non-negative ridge regression – to obtain new weights for each item in the HICP basket, and rescale the items so that the resulting estimate is the most predictive of future headline inflation.[10] In a recent application to seven major euro area countries, Greso and Klieber (2024) confirm Albacore's strong performance in predicting medium-term inflation developments.

According to Goulet Coulombe et al. (2024), Albacore fits the following penalised regression:

$$\hat{w}_c = \arg\min_{w} \sum_{t=1}^{T-h} (\pi_{t+1:t+h} - w'\Pi_t)^2 + \lambda \sum_{c=1}^{K} (w - w_{HICP})^2 \;\; st: \; w \geq 0, w'\iota = 1, \tag{5}$$

where $\hat{w}_c$ are the new optimal weights, h is the forecast horizon and T is the last observation used to train the model. Furthermore, $\pi_{t+1:t+h}$ is the average future headline inflation up to h forecast horizons and Π_t is the matrix of item-related price changes. w_{HICP} is the non-negative HICP weight (adding up to 1) and $K = 92$ is the total number of COICOP-4 items as described in Section 2.1. The first term on the right-hand side of Equation (2.3.2) is the sum of squared residuals, and the last is the penalised term.

[9] Specifically, the PCCI is computed as the average of estimates of two to eight dynamic factors and four to 16 static factors (Bańbura and Bobeica, 2020). The PCCI estimate for Germany is robust to the maximum number of static factors employed (e.g. 4, 8 or 16).

[10] Recently, the authors have been publishing regular updates of their Albacore measures for the US, Canada and the euro area aggregate: https://the-test-of-time.com/albacore-an-indicator-for-core-inflation/

The latter provides the best model fit by optimising the coefficients while avoiding over-fitting of the model. The penalty term, λ, is adjusted by cross-validation. The resulting underlying inflation measure is $Albacore_{comps}$.

A second version of Albacore proposed by Goulet Coulombe et al. (2024) uses the empirical order statistics of the HICP items as regressors. This involves trimming across items (symmetric or asymmetric) via their ranks, along with optimising their weights. The resulting $Albacore_{ranks}$ measure temporarily excludes some items based on the distribution of price changes. Specifically, at each point in time, price changes are ranked from lowest to highest and an estimation is carried out as follows:

$$\hat{w_r} = \arg\min_{w} \sum_{t=1}^{T-h} (\pi_{t+1:t+h} - w' O_t)^2 + \lambda \sum_{r=1}^{K} (w_r - w_{r-1})^2 \;\; st: \; w \geq 0, \; \bar{\pi}_{t+1:t+h} = \bar{\pi}^*_{ranks,t}, \quad (6)$$

where O_t is the matrix which contains the items ranked from lowest to highest at each point in time. The term $\sum_{r=1}^{K} (w_r - w_{r-1})^2$ is the Ridge penalty, which allows for a smooth weighting of the components. The main difference between the two approaches is that $Albacore_{comps}$ only optimises the weights in a manner that maximises the predictive power of the aggregated measure for future headline inflation. In contrast, $Albacore_{ranks}$ takes into account not only the weights, but also the ranks, through symmetric or asymmetric trimming of the items at each point in time.[11]

Note that the model is based on *training-on-purpose*, meaning that the result is maximally predictive of future headline inflation for the respective forecast period. While, in principle, any period could be selected, we train the model with $h = 12$ for one-year ahead inflation which is more in line with a medium-term perspective and comparable to the euro area country application of Albacore by Greso and Klieber (2024).

Like the PCCI, Albacore is based on an estimation procedure and is therefore subject to revision as new inflation data are released. Moreover, as pointed out by Greso and Klieber (2024) – as with any forecasting model – outlier adjustment might affect the estimate of Albacore.[12] To be comparable with the other underlying inflation methods in this note, we limit the outlier adjustment and exclude only the COICOP-4 item 07.3.5, which exhibits strong base effects due to the introduction of a discounted public transport ticket ("Deutschland-Ticket") as of summer 2022.

[11] By replacing $w'\iota = 1$ with $\bar{\pi}_{t+1:t+h} = \bar{\pi}^*_{ranks,t}$ allows for asymmetric trimming of price changes. Including $w'\iota = 1$ would evenly distribute weights around the mean, preventing asymmetry. See Goulet Coulombe et al. (2024) for further details.

[12] For series with large irregularities, the authors either remove severe outliers or replace them with their two- or three-digit counterparts, leaving 66 series for Germany.

2.3.3 Sticky-Price Indicator

As a third underlying inflation measure, we consider a Sticky-Price indicator following Bryan and Meyer (2010), which focuses on items in the CPI that change relatively slowly. In particular, this measure only includes items that have a structurally lower frequency of price changes, as derived from micro price data. The authors argue that the sticky-price indicator appears to incorporate a component of inflation expectations and is therefore more forward-looking than its flexible counterpart. In that sense, Bryan and Meyer (2010) find that sticky-price data improves the forecast of headline inflation for the US.[13] By potentially providing signals for judging the direction of future inflation, we include the sticky-price indicator in our set of underlying inflation measures.

In constructing a sticky-price measure for Germany, we use evidence on price setting from German micro price data. The latter were used in Gautier et al. (2024) to document stylized facts on the frequency and size of price changes in eleven euro area countries. The German CPI micro dataset contains more than 70 million of observations for the period 2010M1-2019M12. Note that the period covered is characterised by a relatively low and stable inflation rate in all euro area countries.

Frequency statistics by Gautier et al. (2024) for Germany are available for 239 items at the COICOP-5 level.[14] In a first step, these results are aggregated to the COICOP-4 level by simple averaging. In a second step, we define a COICOP-4 item as sticky, when its frequency of price changes is equal to or less than the median value among all COICOP-4 items.[15] Excluding energy and food items leaves us with 38 COICOP-4 items, which are classified as sticky.[16] Finally, the sticky-price items are aggregated using the chain linking and annual weighting method of the HICP.

A disadvantage of the sticky-price indicator is its assumption, that the frequency of items is relatively stable across time, at least concerning its ratio to the price setting of more flexible items. Moreover, as it excludes some items on the basis of their characteristics, it suffers from the same drawbacks as the exclusion-based measures of underlying inflation in section 2.2.

[13] A similar measure is published regularly by the Federal Reserve Bank of Atlanta. See `https://www.atlantafed.org/research/inflationproject/stickyprice`.

[14] For this purpose, we use the cross-sectional frequency statistics (including sales) by Gautier et al. (2024); their data and replication files can be accessed here: `https://doi.org/10.3886/E188683V1`.

[15] In particular, the median frequency of price changes at the COICOP-4 level in Germany is 6.3%. Thus, on average, only 6.3% of individual product prices change in a given month.

[16] See Table A1 in the Appendix. Note that the CPI microdata set lacks information on 9 COICOP-4 items, where we have to make some assumptions about whether they are sticky or flexible (marked by a "$\star$" in Table A1).

2.3.4 Supercore

Finally, an alternative underlying inflation measure is Supercore, following Fröhling and Lommatzsch (2011) and Ehrmann et al. (2018). This measure has a direct link to macroeconomic developments, as it is based only on those core items in the HICP (`HICPXEF`), which are sensitive to the output gap. In particular, we regress the seasonally adjusted month-on-month rate of change of a given HICP item on the output gap:

$$y_{i,t} = \alpha_0 + \alpha_1 y_{i,t-1} + \sum_{j=1}^{2} \beta_j x_{t-j} + u_t, \tag{7}$$

where $y_{i,t}$ stands for a given COICOP-4 item $i = 1, ...92$, t denotes a given month, and $x_{i,t-j}$, $j = 1, 2$ is the lag of output gap for the respective quarter.[17] According to this regression, a COICOP-4 item is classified as being output-sensitive if the inclusion of the latter in (7) improves the out-of-sample forecasting performance. In doing so, we estimate the model and forecast inflation for one to four quarters ahead and obtain the average Root Mean Squared Error (RMSE). We then compare the average RMSE to a simple AR(1) benchmark model. Since the Covid-pandemic distorts the nexus with the output gap heavily, we restrict the regression of Equation (7) up to December 2019. For Germany, we find that 40 COICOP-4 items can be categorised as being output-sensitive, such as restaurant services and motor cars.[18] Finally, like in the case of the sticky-price indicator, the output-sensitive items are aggregated following the chain-linking and annual weighting method underlying the HICP.

Several shortcomings of the Supercore measure need to be highlighted. First, the output gap is unobserved and typically relies on a filtering technique that is prone to revision. Thus, the Supercore measure is also subject to revision from one period to another, in contrast to traditional exclusion-based measures of underlying inflation. Second, as it is derived only from core items of the HICP (e.g. excluding food and energy prices), the Supercore is susceptible to the same problems as the exclusion-based measures mentioned above. Third, this measure can also be interpreted as reflecting short-term sensitivity to the business cycle. Therefore, in the context of underlying inflation, it may not be well aligned with the medium- to long-term nature of the latter.

[17] The output gap is the deviation of output from potential level in percent (seasonally adjusted), according to internal Bundesbank estimations.

[18] See Table A1 in the appendix. When Equation (7) is estimated with data up to the most recent year, the number of COICOP-4 items drops to only 21 items, covering less than 20% of the HICP basket.

2.3.5 Resulting alternative measures

The alternative underlying inflation measures for Germany are depicted in Figure 2 together with HICPXEF. Evidently, all measures follow a broadly similar pattern over time. Between the early 2000s and 2020, all underlying measures of inflation show a consistent pattern, with year-on-year changes fluctuating within a relatively stable range around 1.5%, albeit with variations in magnitude and volatility. However, there is a marked divergence in the timing and magnitude of the increase during the inflation surge in 2021-22.[19] More recently, all alternative measures reflect a downward trend, with a gradual convergence to lower levels. Nevertheless, the pace of adjustment and the magnitude of the decline vary across indicators and most still remain above their pre-pandemic levels.

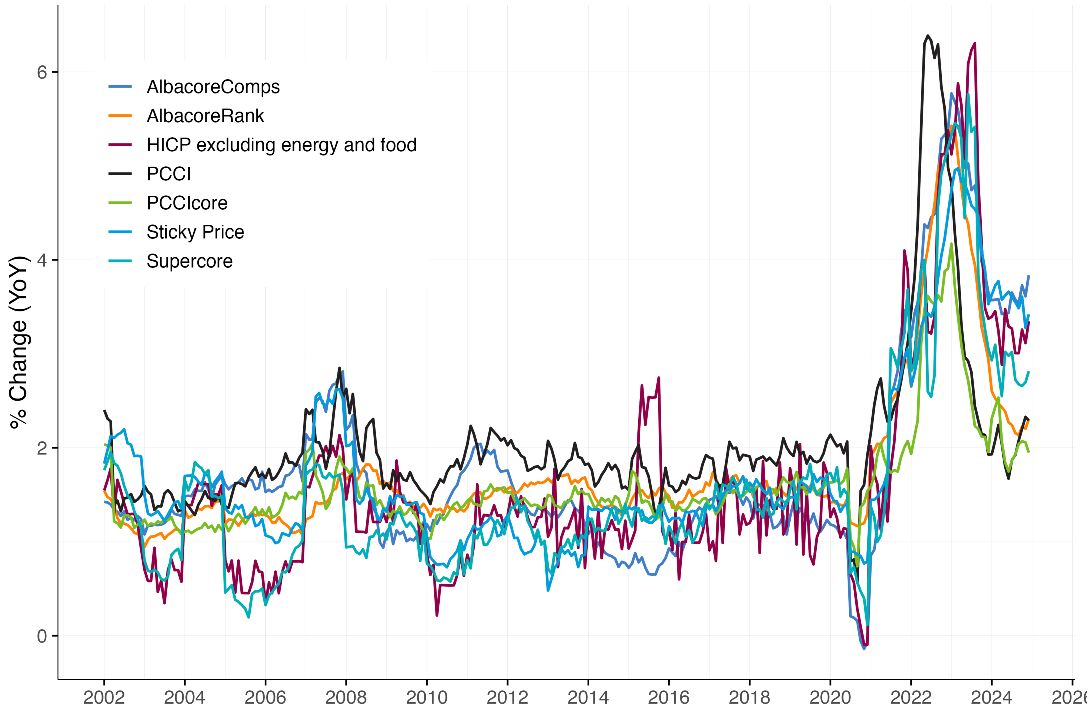


Figure 2: Alternative underlying inflation measures for Germany

[19]The range (min-max values) of the alternative underlying inflation measures for Germany also coincides with the high-inflation period; see Figure 4.

3 Evaluation of underlying inflation measures

Among the desired properties of underlying inflation are low volatility, low bias and good out-of-sample forecasting performance (Goulet Coulombe et al., 2024). These properties are intended to ensure that the underlying inflation measures do not fluctuate much due to noise and temporary shocks, while remaining close to the medium-term value of headline inflation. In these exercises, realized future headline inflation serves as a proxy for underlying inflation, bearing in mind that it might be affected by shocks. To zoom more into the properties and performance of the individual underlying inflation measures, we provide both in-sample and out-of-sample evaluation metrics. Thereby, we follow the methodology of Ehrmann et al. (2018) and Bańbura et al. (2023) for the euro area.

Table 1 reports the sample mean, bias, standard deviation, volatility, and also the root mean square forecast error (RMSFE). The bias is the average difference between each measure and headline inflation, and the volatility is the ratio of the standard deviation of each measure to that of headline inflation. We calculate the RMSFE by comparing 24 months ahead headline inflation with each indicator. Given the substantial shift in the level and volatility of inflation after December 2019, we perform the same analysis on both a subsample to December 2019 and the full sample. Table 1 is sorted with respect to the RMSFE during the sample until 2019, with a lower value indicating better forecasting performance.

Table 1: Evaluation metrics for underlying inflation measures

	Sub Sample (Until 2019)					Full Sample				
UI measure	Mean	Bias	StDev	Vol	RMSFE	Mean	Bias	StDev	Vol	RMSFE
PCCIcore	1.42	-0.12	0.19	0.24	0.76	1.60	-0.49	0.53	0.28	0.79
AlbacoreRank	1.45	-0.07	0.19	0.24	0.78	1.76	-0.34	0.85	0.44	0.81
Sticky Price	1.38	-0.17	0.41	0.52	0.79	1.71	-0.38	0.94	0.49	0.81
PCCI	1.80	0.26	0.28	0.35	0.80	2.03	-0.06	0.86	0.45	0.80
AlbacoreComps	1.41	-0.11	0.41	0.52	0.82	1.78	-0.32	1.12	0.58	0.89
HICPXEFTC	1.06	-0.43	0.46	0.58	0.85	1.44	-0.56	1.13	0.59	0.82
Supercore	1.15	-0.40	0.41	0.52	0.85	1.51	-0.58	1.05	0.55	0.84
Weighted Median	1.32	-0.20	0.36	0.45	0.87	1.76	-0.33	1.36	0.71	0.90
Trim30	1.40	-0.12	0.46	0.58	0.88	1.87	-0.22	1.46	0.76	0.91
HICPXEF	1.11	-0.38	0.52	0.66	0.89	1.48	-0.52	1.16	0.60	0.84
Trim10	1.50	-0.02	0.57	0.72	0.91	2.02	-0.07	1.69	0.88	0.95
HICPXE	1.27	-0.23	0.58	0.73	0.92	1.72	-0.29	1.45	0.76	0.86
HICP	1.49	0.00	0.79	1.00	1.00	2.00	0.00	1.92	1.00	1.00

Note: This table shows evaluation metrics based on the full sample (Jan 2001 to Dec 2024). "Mean" is the mean and "Bias" the average difference between each measure and headline inflation based on the full sample. "StDev" denotes the standard deviation and "Vol" the volatility, which is the ratio of the standard deviation of each measure to that of headline inflation. The table is sorted according to the root mean square forecast error (RMSFE) of the subsample up to 2019. For computing the RMSFE, we use 24-months ahead headline inflation. Lighter colours (small RMSFE values) reflect a better performance.

Regarding the conventional exclusion-based measures of underlying inflation such as `HICPXEF`, we find that these indicators exhibit poor in-sample forecasting performance in terms of the RMSFE compared to our alternative underlying inflation measures, both in the subsample until 2019 and in the full sample. In addition, they tend to have a higher volatility (and thus a higher standard deviation) and a greater bias with respect to headline inflation. For Germany, the best performing exclusion-based measure is `HICPXEFTC`; hence, by excluding the two volatile items clothing and package holidays, some gains can be achieved in terms of the RMSFE.

Among the alternative underlying inflation measures, Supercore demonstrates the weakest forecasting performance in terms of the RMSFE and exhibits the highest volatility (up to 2019). This outcome aligns with expectations, as Supercore is derived from business cycle dynamics, with its limitations becoming particularly apparent during the pandemic, when both domestic and external demand experienced substantial declines. Furthermore, Supercore displays the highest bias in absolute terms. Conversely, the in-sample forecasting performance of $PCCIcore$, *AlbacoreRank*, and the Sticky-Price indicator are notably strong. For the full sample, both PCCI measures and *AlbacoreRank* emerge as the top performers.[20]

Given that the model-based measures seem to be superior to traditional exclusion-based measures from an in-sample perspective, how do they perform in a real-time setting? One advantage of the traditional measures is that revisions don't matter because they are based only on HICP data, which are rarely revised (only in the case of large data errors). This is in contrast to model-based approaches, where estimates may change with each new data release. To this end, we estimate three model-based measures in real time for the period 2018M1-2024M12: Albacore, PCCI and Supercore.[21] In a next step, we compute the RMSFE with respect to headline inflation $h = 12$ and 24 months ahead.

Table 2 reports the out-of-sample forecasting performance of all underlying inflation measures with respect to future headline inflation. The resulting RMSFE is expressed relative to the RMSFE of inflation (`HICP`) itself, and sorted by $h = 24$. Again, the alternative measures generally outperform the traditional measures in terms of forecasting accuracy, with *AlbacoreRank* providing the highest forecasting gain (also at $h = 12$). Nevertheless, the difference between the different measures seems to be relatively small. Among the traditional exclusion-based measures, `HICPXEFTC` seems to be the most informative about future inflation. Comparing each measure individually across horizons, all measures seem to provide more predictive power at the longer horizon.

[20] Note that we trained Albacore for $h = 12$, so even higher gains could be achieved using $h = 24$.

[21] In doing so, the seasonal adjustment is done for each vintage month separately. For Supercore, we abstract from the fact that the first-step regression is based on an estimate of the output gap itself, which should be added to estimation uncertainty in real time. The resulting real-time vintages are shown in Figure A1; they turn out to be the most stable for the two Albacore measures.

Table 2: Out-of-sample forecasting performance of underlying inflation measures: Relative RMSFE

UI measure	h = 12	h = 24
AlbacoreRank	0.89	0.77
Stickyprice	0.91	0.78
Supercore	0.94	0.80
PCCICore	1.00	0.80
HICPXEFTC	0.92	0.81
PCCI	0.92	0.81
HICPXEF	0.95	0.83
AlbacoreComps	0.94	0.84
HICPXE	0.99	0.84
Weighted Median	0.96	0.85
Trim30	0.96	0.86
Trim10	0.98	0.90
HICP	1.00	1.00

Note: This table illustrates the out-of-sample forecasting performance of each individual underlying inflation measure with respect to headline inflation (HICP) at different forecast horizons h. The resulting RMSFE is expressed relative to the one by HICP itself. Lighter colours (small RMSFE values) reflect a better performance.

Finally, an optimal forecast combination exercise shows that there is no single measure outperforming others over time. Similar to Bańbura et al. (2023), we evaluate the optimal forecast combination among measures to minimise the RMSFE for German headline inflation 24 months ahead. As depicted in Figure 4, for each period from 2005M1 to 2022M12, the algorithm tends to favor model-based measures such as $PCCI$ and $AlbacoreRank$ over exclusion-based measures such as Trims, although $HICPXEFTR$ is also selected in certain periods. However, no single measure consistently outperforms the others over time. As a policy implication, the uncertainty related to the performance of individual measures suggests that a range of underlying inflation indicators should be monitored.

When considering a wider range of measures, some valuable insights for inflation dynamics in Germany become evident. While all indicators point to a marked decline in underlying inflation since the peak in late 2022, they remain above historical averages.[22] During the surge, both traditional exclusion-based and alternative model-based measures reached exceptionally high levels, with a notable widening in their range. Although underlying inflation declined in response to monetary tightening, the pace of disinflation has slowed since early 2024, particularly as goods price pressures have largely eased. Differences in timing are especially evident: model-based indicators, in particular the PCCI measure, but also Albacore, identified the turning point towards higher inflation rates

[22] Concerning the alternative measures, the $AlbacoreComps$ measure has been just over 1 percentage point above the other measures in this group for a few months now. Without this measure, the band of alternative measures is even slightly below that of traditional measures.

already at the beginning of 2021 – somewhat earlier than the traditional measures. The turning point towards the recent disinflation process also became apparent somewhat earlier in the alternative measures.

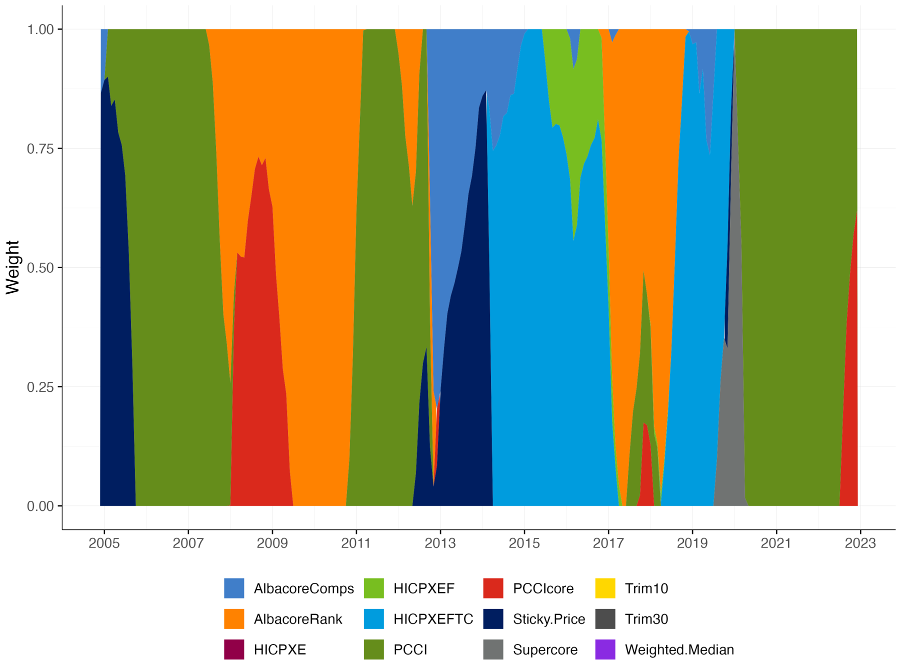
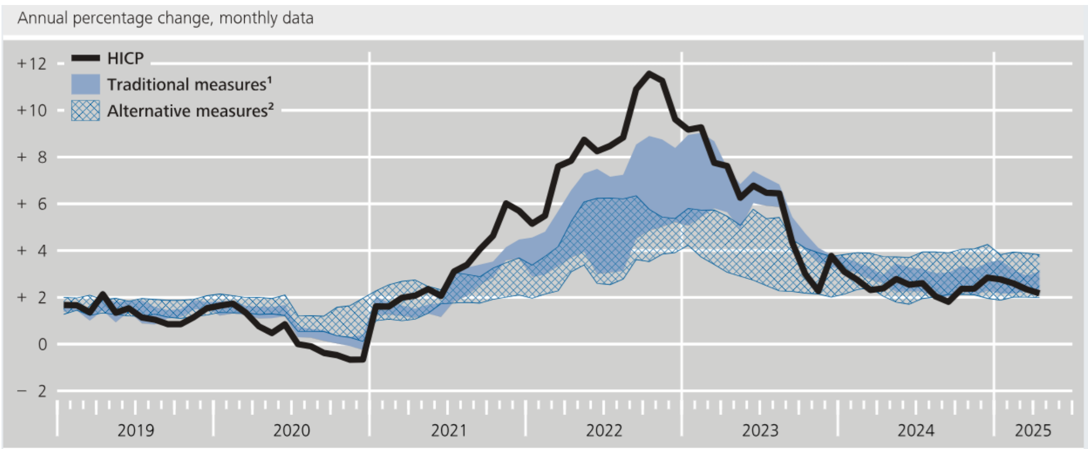


Figure 3: Optimal forecast combination weights of underlying inflation measures

Note: This figure shows the optimal forecasting weights by minimising the RMSFE over a three-year rolling window for combining underlying inflation measures to forecast headline inflation 24 months ahead.



Sources: Eurostat, Destatis and Bundesbank calculations. **1** HICP excluding energy, HICP excluding energy and (unprocessed) food, HICP excluding energy, food, travel and clothing, and trimmed means (trimmed by 10%, 30% and weighted median). **2** PCCI and PCCI core, Albacore (rank and comps), sticky price indicator and supercore.
Deutsche Bundesbank

Figure 4: Range of measures of underlying inflation in Germany

4 Sensitivity of measures to monetary policy shocks

As discussed before, many central banks closely monitor underlying inflation measures to derive information about the stance of the inflation trend. In addition, underlying inflation measures are sometimes used to diagnose whether monetary policy is effective. For this reason, it can be useful to know whether and to what extent underlying inflation measures react to monetary policy measures.

One challenge in identifying the impact of monetary policy shocks on underlying inflation measures is that our measures are calculated in terms of year-on-year growth rates. To avoid relating the monetary policy shocks in the current month to price developments over the past twelve months rather than to price changes in the future, we transform the variables into cumulative price changes. This can be achieved by re-writing the dependent variable in long differences.[23] In what follows, we denote inflation π_t as:

$$\pi_t = (P_t - P_{t-12})/P_{t-12} \tag{8}$$

where P_t is the level of the price index in month t. The cumulative changes are $\frac{P_T - P_{t-1}}{P_{t-1}}$, where T is the period of choice (e.g. 12, 24 or 36 months). To take the cumulative percentage change in prices (twelve periods), we simply shift annual inflation by eleven periods:

$$\Delta p_{t+11} = \frac{P_{t+11} - P_{t-1}}{P_{t-1}} = \pi_{t+11} \tag{9}$$

where Δp_{t+h} measures the cumulative change in prices in period h relative to $t-1$. Similarly, we take the cumulative impact for two years (24 months) by adding and subtracting

[23] We refer the reader to Jordà (2023) for transformations of variables and recent applications of local projections in economics and to Allayioti et al. (2024) using the same same shock series to study the credit channel of monetary policy in the setting of local projections with long differences.

P_{t+11} as an intermediate term:

$$\begin{aligned}
\Delta p_{t+23} &= \frac{P_{t+23} - P_{t-1}}{P_{t-1}} \\
&= \frac{P_{t+23} - P_{t+11} + P_{t+11} - P_{t-1}}{P_{t-1}} \\
&= \frac{P_{t+23} - P_{t+11}}{P_{t-1}} + \frac{P_{t+11} - P_{t-1}}{P_{t-1}} \\
&= \frac{P_{t+23} - P_{t+11}}{P_{t-1}} + \pi_{t+11} \\
&= \frac{P_{t+23} - P_{t+11}}{P_{t+11}} \times \frac{P_{t+11}}{P_{t-1}} + \pi_{t+11} \\
&= \pi_{t+23} \left[\frac{P_{t+11}}{P_{t-1}} - 1 + 1 \right] + \pi_{t+11} \\
&= \pi_{t+23} \left[\frac{P_{t+11} - P_{t-1}}{P_{t-1}} + 1 \right] + \pi_{t+11} \\
&= \pi_{t+23}(\pi_{t+11} + 1) + \pi_{t+11} \\
&= (1 + \pi_{t+23})(1 + \pi_{t+11}) - 1
\end{aligned}$$

In a similar vein, the cumulative price change for 36 periods can be calculated as $\Delta p_{t+35} = (1 + \pi_{t+11})(1 + \pi_{t+23})(1 + \pi_{t+35}) - 1$.

Hence, the cumulative price change can be calculated by multiplicative terms of inflation measure at different periods. After obtaining the price changes in cumulative terms, we estimate the following local projections:

$$\Delta p_{t+h} = \beta_{0,h} + \beta_{1,h}\Psi_t + \beta_{2,h}\Gamma_t + \xi_{t,h} \tag{10}$$

where h is the horizon, Δp_{t+h} measures the cumulative price change at period h relative to period $t-1$, Ψ_t is the exogenous monetary policy shock as proposed by Jarociński and Karadi (2020), Γ_t is vector of controls and ξ_t is the error term. $\beta_{1,h}$ is the coefficient of interest and measures the causal impact of monetary policy shock in each horizon.

Our key variable of interest, the exogenous monetary policy shock proposed by Jarociński and Karadi (2020), distinguishes between the effects of monetary policy stemming from the central bank's information set and the direct effects of monetary intervention. In our baseline specification, we include twelve lags of the monetary policy shock and three lags of other macroeconomic variables as controls (industrial production, the unemployment rate, oil prices and the real effective exchange rate for Germany).[24] Our sample period is January 2002 to October 2023; since it covers the Covid-19 pandemic, we also in-

[24] See Table B1 for a definition of macroeconomic variables used.

clude a dummy for the period from March to August 2020 to control for pandemic-related dynamics. In this respect, our empirical specification is most similar to Holm et al. (2021) and Cloyne et al. (2022), who examine the impact of Bundesbank monetary policy shocks on the German economy in the pre-euro area period.

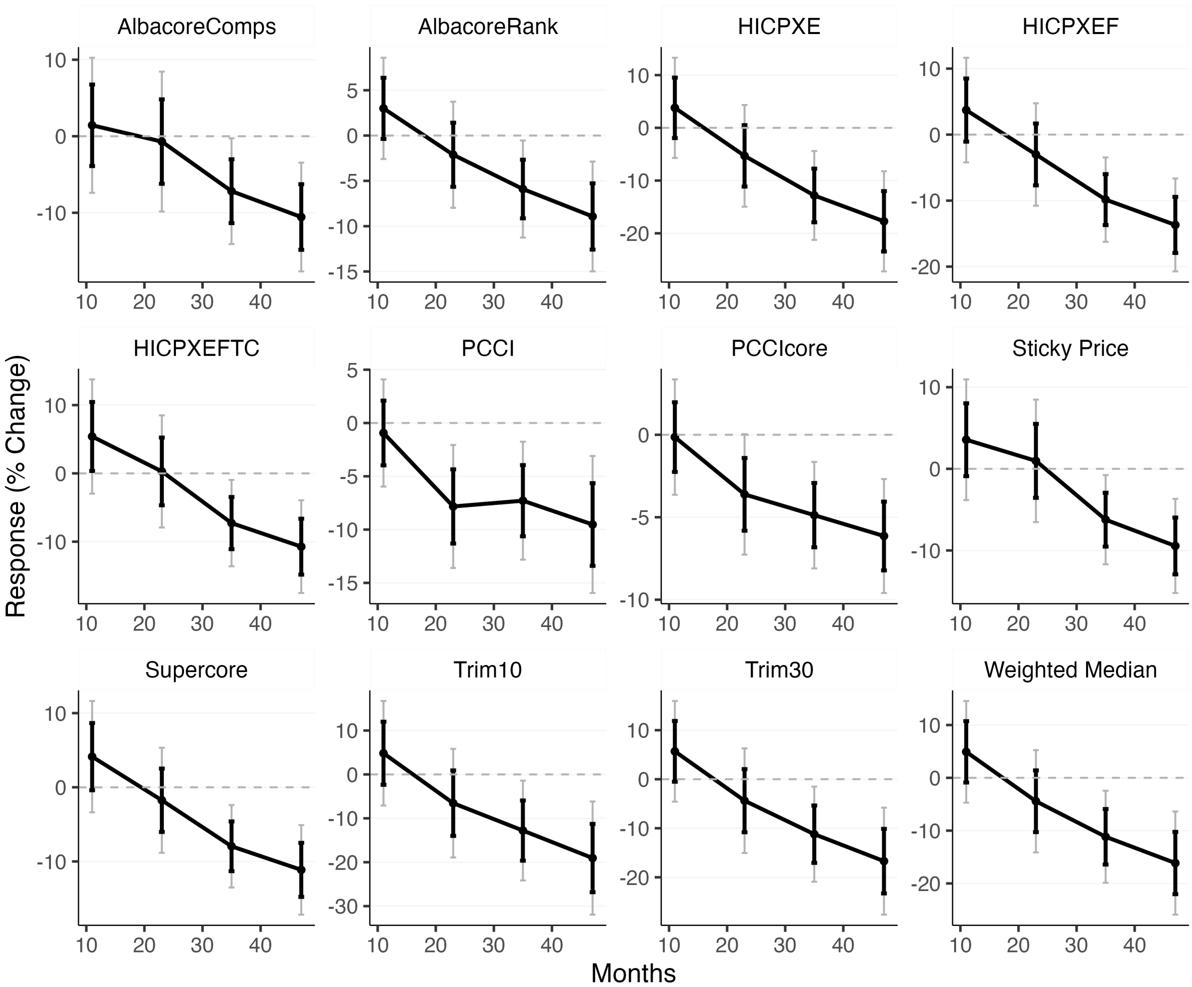


Figure 5: Cumulative responses of underlying inflation measures to a monetary policy shock

Note: This figure presents the cumulative responses of underlying inflation measures to euro area-wide monetary policy shocks as proposed by Jarociński and Karadi (2020). The solid line indicates the point estimate, while the black and grey error bars indicate the 68% and 90% confidence intervals, respectively. The sample period is 2002M1-2023M10. The estimation includes twelve lags of the monetary policy shock, and three lags of industrial production, unemployment, oil prices and the real effective exchange rate. A dummy variable for 2020M3-2020M8 is included to control for pandemic-related dynamics.

Figure 5 presents the baseline results of Equation (10). The solid line indicates the point estimate, with the black and grey error bars representing the 68% and 90% confidence intervals, respectively. As expected, all underlying inflation measures fall in response to a contractionary monetary policy shock. The bulk of this decline occurs within 36 months, after which the effect of monetary policy has largely dissipated. While the magnitude of the responses is heterogeneous across measures, the overall pattern remains consistent: Tighter monetary policy exerts a downward pressure on underlying inflation indicators over a period of one to three years, with heterogeneity in the timing and intensity of these effects. Our results also align with Cloyne et al. (2022), who document that it takes more than a year for consumer prices to respond to monetary policy shocks for Germany.

Our results are also confirmed when considering different lags, excluding control variables and a restricted sample period. To this end, we run several different specifications, similar to Cloyne et al. (2022): First, we include only the monetary policy shock as a dependent variable (see Figure B1 in the appendix) and also restrict the sample to 2019M12 to avoid the post-COVID period (Figure B2). Second, we estimate Equation (10) with only six lags of the monetary policy shock (Figure B3) and restrict the sample to 2019M12 (Figure B4). The results show a gradual decline in prices ranging from 3% to 7.5% over a period of 36 months. After this decline, the effects of the monetary policy shocks largely disappear. While there are slight changes in the magnitude across the different specifications, the main message remains the same: our underlying measures of inflation are also highly responsive to monetary policy shocks.

5 Conclusion

In this paper, we evaluate various underlying inflation measures for Germany, using standard (exclusion-based) measures and more sophisticated measures derived from econometric models and machine learning techniques or derived from micro-data evidence. We then compare this set of measures using in-sample and out-of-sample evaluation metrics. We find that, compared to traditional exclusion-based measures, the set of alternative underlying inflation measures has generally a lower volatility, a lower bias and a higher out-of-sample forecasting accuracy. Finally, we show that according to all measures under consideration, underlying inflation is highly sensitive to monetary policy shocks and declines in response to a contractionary shock.

From the set of alternative measures, we do not find evidence that there is a single measure which clearly outperforms the others over time. This becomes notably evident, when including the post-Covid period in our sample, which is characterised by a higher macroeconomic volatility. However, the range of alternative indicators seems to have identified the turning points towards higher inflation and the subsequent disinflation process somewhat earlier than the traditional ones. Overall, our results confirm previous findings by Ehrmann et al. (2018) for the euro area, implying for policy makers that a range of model-based measures should be taken into account when monitoring underlying inflation.

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A Appendix

Table A1: COICOP-4 items used in constructing underlying inflation measures

COICOP	COICOP-4 Title	Special Agg.	Weight	HICPX E	HICPX EF	HICPX EFTC	Super-core	Sticky Price
0111	Bread and cereals	Food	19.87	1	0	0	0	0
0114	Milk, cheese and eggs	Food	19.76	1	0	0	0	0
0115	Oils and fats	Food	3.56	1	0	0	0	0
0118	Sugar, jam, honey, chocolate and confectionery	Food	8.41	1	0	0	0	0
0119	Food products n.e.c.	Food	6.13	1	0	0	0	0
0121	Coffee, tea and cocoa	Food	4.75	1	0	0	0	0
0122	Mineral waters, soft drinks, fruit and vegetable juices	Food	10.64	1	0	0	0	0
0211	Spirits	Food	3.27	1	0	0	0	0
0212	Wine	Food	6.86	1	0	0	0	0
0213	Beer	Food	5.49	1	0	0	0	0
0220	Tobacco	Food	17.38	1	0	0	0	0
0112	Meat	Food	24.02	1	0	0	0	0
0113	Fish	Food	4.5	1	0	0	0	0
0116	Fruit	Food	12.18	1	0	0	0	0
0117	Vegetables	Food	15.21	1	0	0	0	0
0511	Furniture and furnishings	NEIG	25.86	1	1	1	0	0
0512	Carpets and other floor coverings	NEIG	1.92	1	1	1	1	1
0531-2	Major household appliances, small electric hous. appl.	NEIG	8.85	1	1	1	1	0
0711	Motor cars	NEIG	35.18	1	1	1	1	0
0712-4	Motor cycles, bicycles and animal drawn vehicles	NEIG	7.35	1	1	1	0	0
0911	Equip. for reception, recording and reprod. of sound and pictures	NEIG	8.11	1	1	1	0	0
0912	Photographic and cinematographic equip. and optical instruments	NEIG	0.94	1	1	1	1	0
0913	Information processing equipment	NEIG	6.76	1	1	1	0	0
0921-2	Major durables for in/outdoor recreation incl. musical instr.	NEIG	3.32	1	1	1	0	0
1231	Jewellery, clocks and watches	NEIG	4.95	1	1	1	0	1
0431	Materials for the maintenance and repair of the dwelling	NEIG	5.01	1	1	1	0	1
0441	Water supply	NEIG	5.1	1	1	1	0	1
0561	Non-durable household goods	NEIG	6.23	1	1	1	1	0
0611	Pharmaceutical products	NEIG	9.53	1	1	1	1	0
0612-3	Other medical products, therapeutic appliances and equipment	NEIG	13.87	1	1	1	1	0
0933	Gardens, plants and flowers	NEIG	9.06	1	1	1	1	0
0934-5	Pets and related prod. incl. veterinary and other serv. for pets	NEIG	9.91	1	1	1	0	1
0952	Newspapers and periodicals	NEIG	5.62	1	1	1	1	1
0953-4	Misc. printed matter and stationery and drawing materials	NEIG	5.66	1	1	1	1	0
1212-3	Electric appliances and other appliances etc. for pers. Care	NEIG	12.81	1	1	1	1	0
0311	Clothing materials	NEIG	0.45	1	1	0	0	1
0312	Garments	NEIG	35.52	1	1	0	1	0
0313	Other articles of clothing and clothing accessories	NEIG	1.28	1	1	0	1	0
0320	Footwear	NEIG	7.68	1	1	0	1	0
0520	Household textiles	NEIG	5.72	1	1	1	1	0
0540	Glassware, tableware and household utensils	NEIG	7.57	1	1	1	1	0
0550	Tools and equipment for house and garden	NEIG	6.26	1	1	1	0	1
0721	Spare parts and accessories for personal transport equipment	NEIG	10.14	1	1	1	0	0
0914	Recording media	NEIG	1.91	1	1	1	1	0
0931	Games, toys and hobbies	NEIG	5.46	1	1	1	1	0
0932	Equipment for sport, camping and open-air recreation	NEIG	4.66	1	1	1	1	0
0951	Books	NEIG	4.04	1	1	1	0	1
1232	Other personal effects	NEIG	3.39	1	1	1	0	0
0451	Electricity	Energy	33.18	0	0	0	0	0
0452	Gas	Energy	18.01	0	0	0	0	0
0453	Liquid fuels	Energy	4.84	0	0	0	0	0
0454	Solid fuels	Energy	0.86	0	0	0	0	0
0455	Heat energy	Energy	4.46	0	0	0	0	0
0722	Fuels and lubricants for personal transport equipment	Energy	43.25	0	0	0	0	0
0410	Actual rentals for housing	Services	72.65	1	1	1	1	1
0432	Services for the maintenance and repair of the dwelling	Services	4.58	1	1	1	1	1
0442	Refuse collection	Services	4.23	1	1	1	1	1
0443	Sewerage collection	Services	5.1	1	1	1	1	1
0444	Other services relating to the dwelling n.e.c.	Services	12.81	1	1	1	1	1
0513	Repair of furniture, furnishings and floor coverings	Services	0.54	1	1	1	1	1
0533	Repair of household appliances	Services	0.36	1	1	1	1	1
0562	Domestic services and household services	Services	5.13	1	1	1	0	0
1252	Insurance connected with the dwelling	Services	1.94	1	1	1	0	1*
0723	Maintenance and repair of personal transport equipment	Services	22.49	1	1	1	1	1

COICOP	COICOP-4 Title	Special Agg.	Weight	HICPX E	HICPX EF	HICPX EFTC	Super-core	Sticky Price
0724	Other services in respect of personal transport equipment	Services	16.66	1	1	1	1	1
0731	Passenger transport by railway	Services	9.58	1	1	1	0	1*
0732	Passenger transport by road	Services	2.9	1	1	1	0	1
0733	Passenger transport by air	Services	6.76	1	1	0	0	0*
0734	Passenger transport by sea and inland waterway	Services	1.17	1	1	1	0	0
0735	Combined passenger transport	Services	11.69	1	1	1	1	0
0736	Other purchased transport services	Services	0.76	1	1	1	1	1
1254	Insurance connected with transport	Services	8.3	1	1	1	0	0
0810	Postal services	Services	2.06	1	1	1	1	1*
0830	Telephone and telefax services	Services	17.55	1	1	1	1	1*
0820	Telephone and telefax equipment	Services	4.31	1	1	1	1	0
0314	Cleaning, repair and hire of clothing	Services	0.75	1	1	0	1	1
0960	Package holidays	Services	33	1	1	0	0	0*
1120	Accommodation services	Services	18.35	1	1	0	0	0
0915	Repair of audio-visual, photographic, info. processing equip.	Services	0.21	1	1	1	0	1
0923	Mainten. and repair of other major durab. for recreat. and culture,	Services	0.16	1	1	1	0	1*
0941	Recreational and sporting services	Services	9.52	1	1	1	1	1
0942	Cultural services	Services	8.23	1	1	1	0	1
1111	Restaurants, cafes and the like	Services	48.68	1	1	1	1	1
1112	Canteens	Services	5.93	1	1	1	0	1
1211	Hairdressing salons and personal grooming establishments	Services	11.45	1	1	1	1	1
1000	Education	Services	7.73	1	1	1	0	1
0621-3	Medical and paramedical services	Services	15.32	1	1	1	0	1
0622	Dental services	Services	7.31	1	1	1	1	0
0630	Hospital services	Services	10.32	1	1	1	1	0
1240	Social protection	Services	30.12	1	1	1	0	0
1253	Insurance connected with health	Services	8.43	1	1	1	0	1
1255	Other insurance	Services	4.11	1	1	1	0	1*
1260	Financial services n.e.c.	Services	12.77	1	1	1	1	1*
1270	Other services n.e.c.	Services	9.29	1	1	1	0	1
Total	number of COICOP-4 items		94	88	73	65	40	38
Total	HICP weight in per mille (as of 2024)		1000	895	733	630	456	360

Note: This table shows which COICOP-4 item are included in the calculation of a given underlying inflation measure. For Supercore, the classification of COICOP-4 items is reported according to the pre-Covid estimation. For the Sticky-Price indicator, we have manually classified 9 COICOP-4 items, which are not reported in Gautier et al. (2024) for Germany, as being sticky or flexible, marked by a “⋆”.

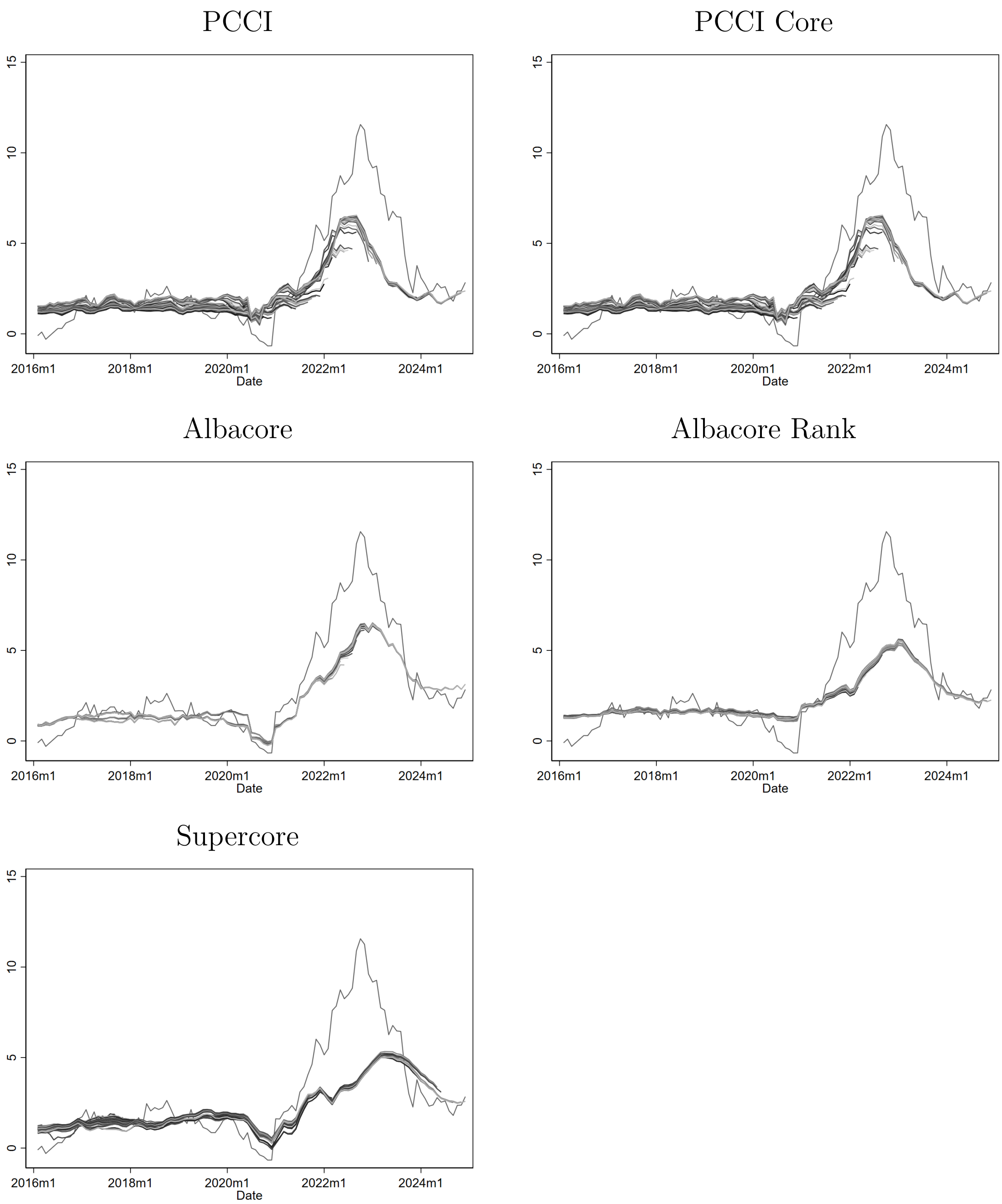

Figure A1: Real-time vintages of model-based underlying inflation measures

Note: This figure presents the real-time vintages for the period 2018M1-2024M12 of the alternative model-based underlying inflation measures (grey lines) as described in Section 2.3. The blue line indicates the year-on-year official HICP inflation rate.

B Local Projection Exercise

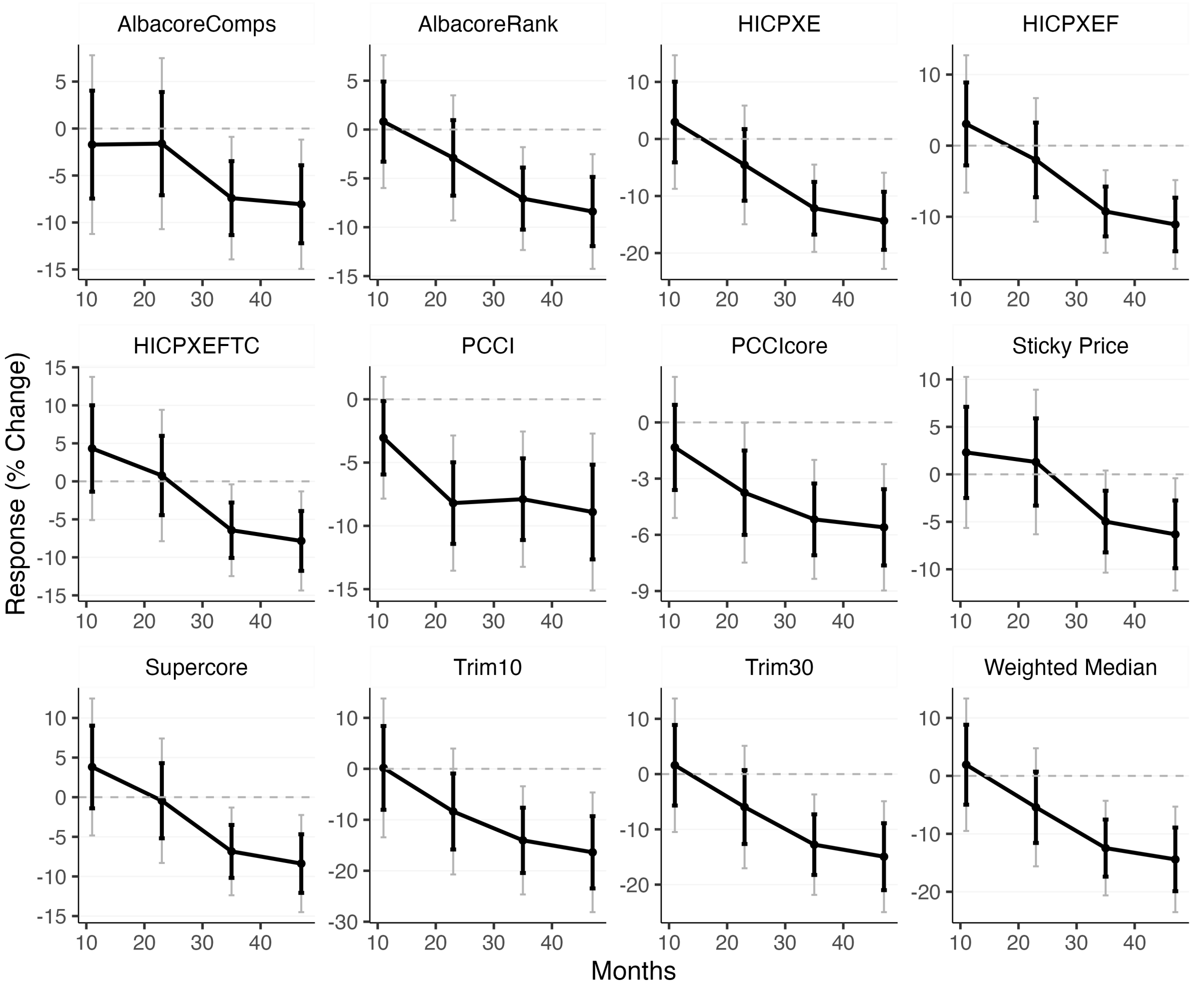

Figure B1: Cumulative responses of underlying inflation measures to a monetary policy shock

Note: This figure presents the cumulative responses of underlying inflation measures to a euro area-wide monetary policy shock by Jarociński and Karadi (2020). The solid line indicates the point estimate, with the black and grey error bands denoting the 68% and 90% confidence intervals, respectively. The estimation includes only twelve lags of monetary policy shocks. Other variables are excluded. The sample period is 2002M1-2023M10.

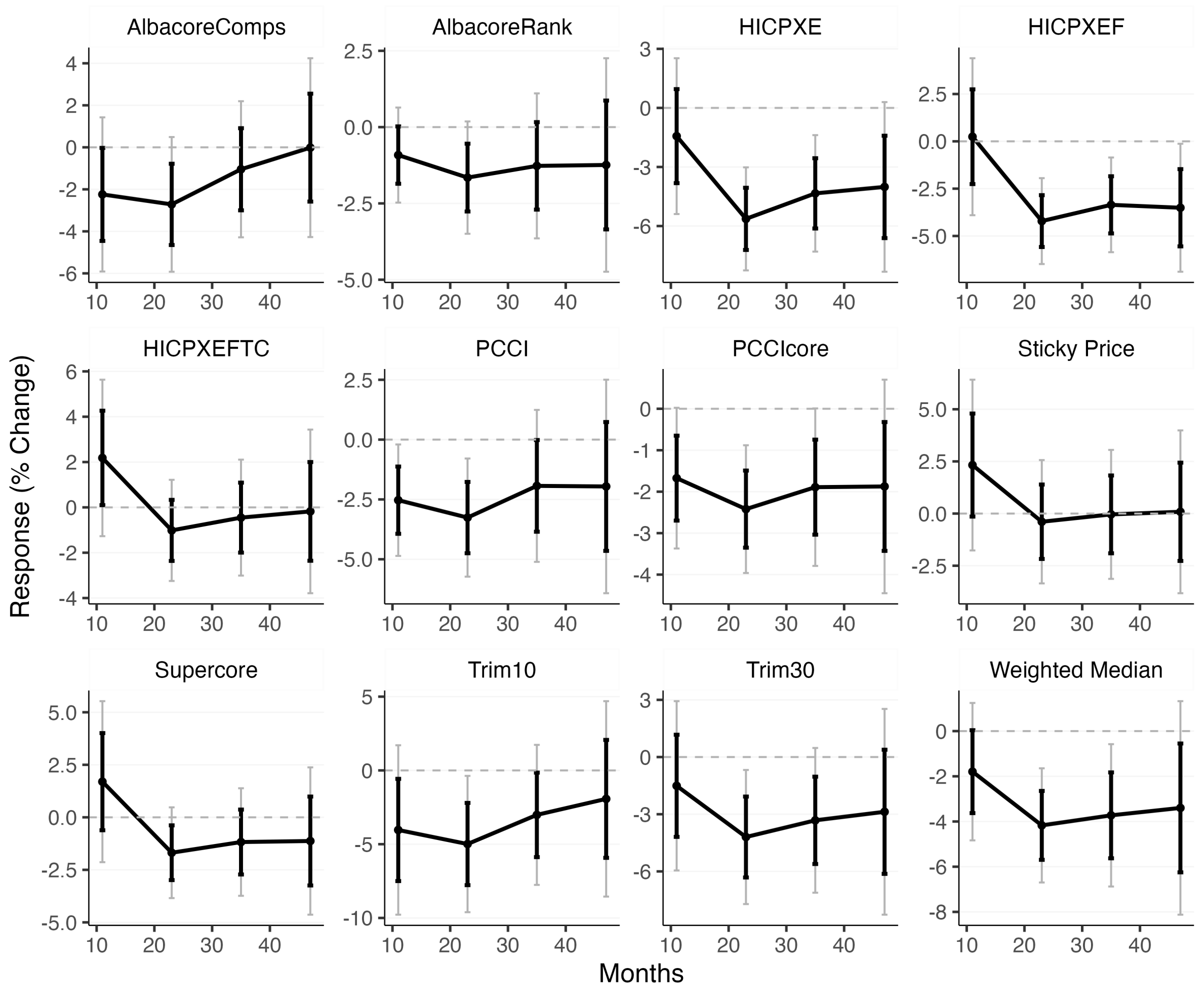

Figure B2: Cumulative responses of underlying inflation measures to a monetary policy shock

Note: This figure presents the cumulative responses of underlying inflation measures to a euro area-wide monetary policy shock by Jarociński and Karadi (2020). The solid line indicates the point estimate, with the black and grey error bands denoting the 68% and 90% confidence intervals, respectively. The estimation includes only twelve lags of monetary policy shocks. Other variables are excluded. The sample period is 2002M1-2019M12.

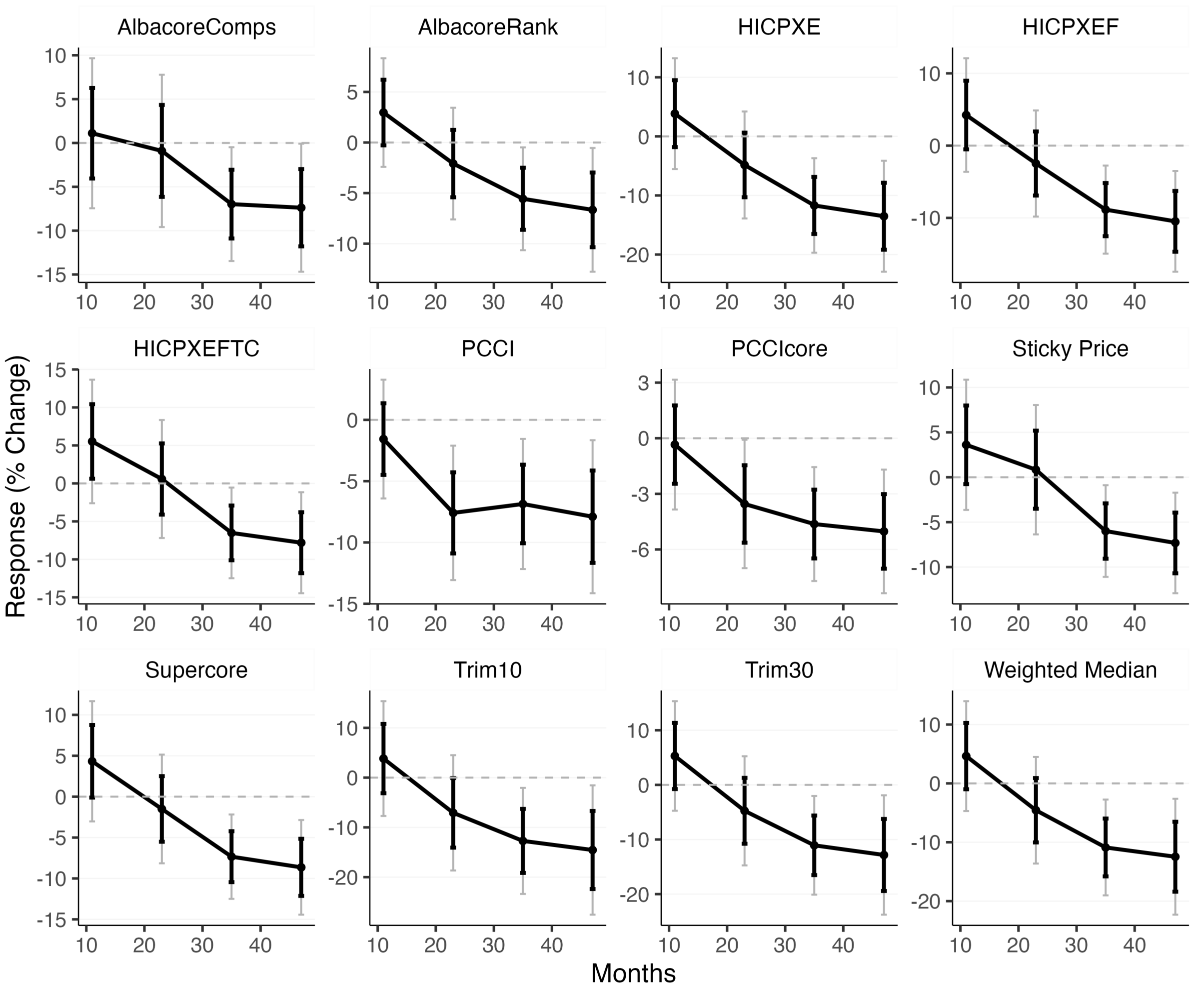

Figure B3: Cumulative responses of underlying inflation measures to a monetary policy shock

Note: This figure presents the cumulative responses of underlying inflation measures to a euro area-wide monetary policy shock by Jarociński and Karadi (2020). The solid line indicates the point estimate, with the black and grey error bands denoting the 68% and 90% confidence intervals, respectively. The estimation includes six lags of the monetary policy shock, and three lags of industrial production, unemployment, oil prices and the real effective exchange rate. A dummy variable for 2020M3-2020M8 is included to control for pandemic-related dynamics. The sample period is 2002M1-2023M10.

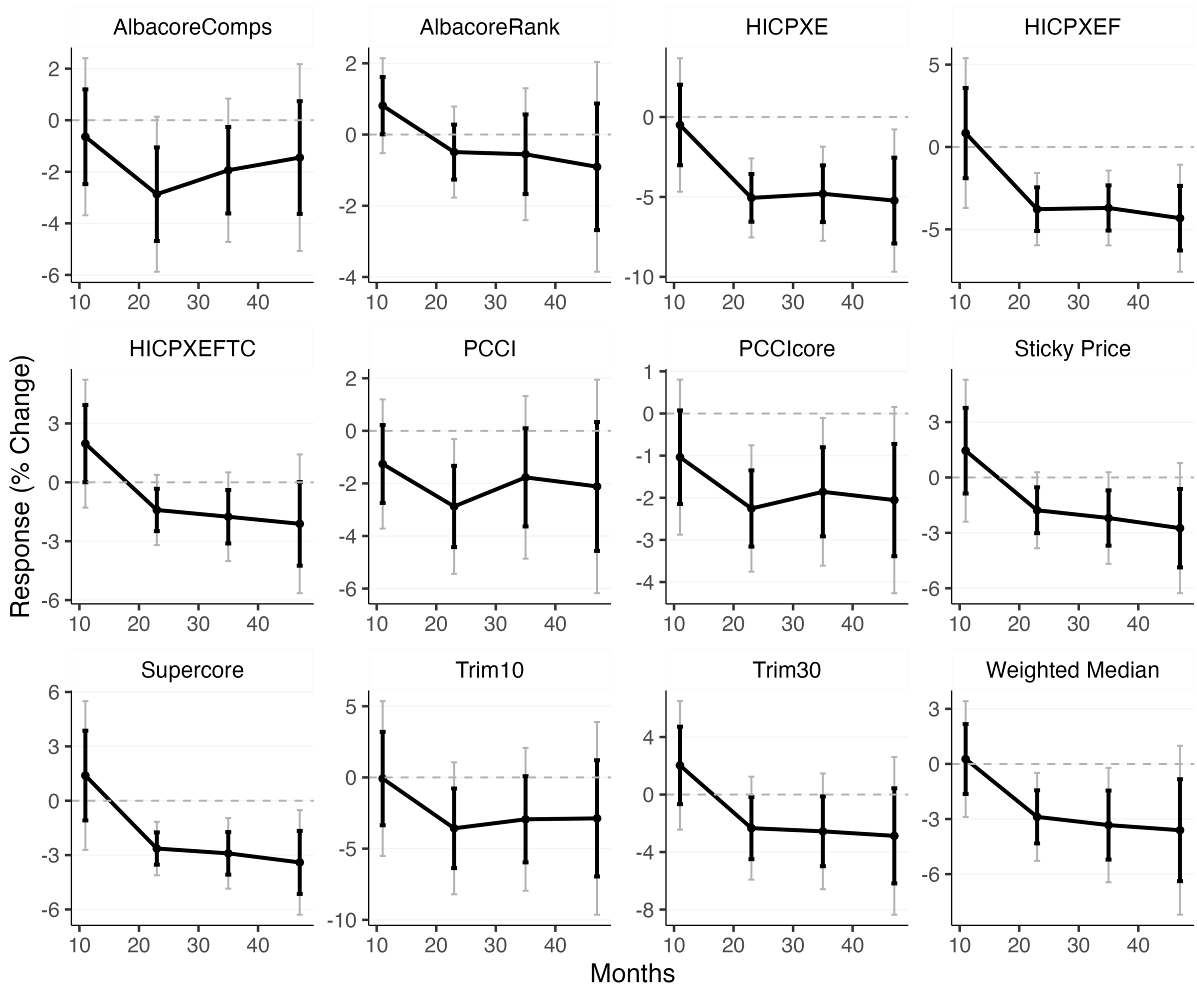

Figure B4: Cumulative responses of underlying inflation measures to a monetary policy shock

Note: This figure presents the cumulative responses of underlying inflation measures to a euro area-wide monetary policy shock by Jarociński and Karadi (2020). The solid line indicates the point estimate, with the black and grey error bands denoting the 68% and 90% confidence intervals, respectively. The estimation includes six lags of the monetary policy shock, and three lags of industrial production, unemployment, oil prices and the real effective exchange rate. The sample period is 2002M1-2019M12.

Variable	Definition	Unit	Source note
Brent	Brent oil prices, denominated in EUR, Market place London	Log	LSEG
Real effective exchange rate	Real effective exchange rate (deflator: consumer price indices - 42 trading partners) for Germany	Log	Eurostat, Table ert_eff_ic_m
Industrial Production	Industrial Production	Log, s.a.	Destatis
Unemployment	Unemployment rate, registered pursuant to section 16 Social Security Code III	Percent, s.a.	Bundesagentur für Arbeit
Monetary Policy Shock	Monetary Policy Shock	Level	Jarociński and Karadi (2020), updated series until Oct 2023 available at https://marekjarocinski.github.io/jkshocks/jkshocks.html

Table B1: Definition of macroeconomic variables used in the local projection exercise